Green Logistics : Advanced Methods for Transport Logistics Management Systems Including Platooning and Alternative Fuel Powered Vehicles

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By

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Abstract

Green Logistics has attracted increased attention from researchers during the last few years, due to the growing environmental awareness. Road Transport is a major factor in climate change and accounts for a large proportion of the total UK emissions, including Carbon Dioxide (CO_2). With traffic and congestion levels growing, efficient routing combined with greener (more environmentally friendly) vehicles will be of great importance. The purpose of this thesis is two-fold: i) to provide an insight into Green Logistics and ways in which green technologies can be combined within the vehicle routing problem and ii) identifying new variants of the Vehicle Routing Problem (VRP) that can be applied to real-life instances; The Platooning Routing Problem with Changing Split Points, and the proposition of a Hyper-Realistic Electric Vehicle Energy Consumption model that can be applied to the E-VRP. A thorough CO_2 experiment was also conducted on a rolling road, providing useful data that future research can use to further increase the accuracy of routing models. The platooning of vehicles proves to be an important technique that can lead to large decreases in fuel consumption and can be easily implemented in most transport systems; the process requires advanced and accurate computer systems that are only now becoming available to manufacturers. The Platooning model is designed and tested within this thesis and it is hoped to spark further interest in this crucial area of research. Extensions to the Platooning Problem include the addition of heterogeneous fleets and how they change the dynamics of the proposed problems, as well as further work on the placement of the critical splitting point. Allowing the consideration of using limited range Electric Vehicles (EVs) as well as Conventional Vehicles (CVs) and Alternative Fuel powered Vehicles (AFVs) can further increase the emission savings and are becoming progressively popular in today's society. We therefore have carried out extensive research around the area of AFV's including detailed battery specifics for EV's. The objective is to minimise the amount of emissions while satisfying the time window requirements of customers maintaining low overall financial costs. The resulting emissions are largely affected by the electricity fuel mix of the country, we found that the indirect EV emissions for a 30kwh EV can vary by as much as 33% throughout the day and as much as 68% throughout the year with different seasons. Various heuristic and metaheuristic solution techniques as well as several classical heuristics are implemented including the Clarke and Wright Savings heuristic algorithm (CWSA), the Sweep Algorithm and the Variable Neighbourhood Search (VNS) method. These heuristic and metaheuristic models are tested on the Christofides et al. datasets and we achieve solutions that are on average 1.67% and 8.5% deviated from the best-known solution for unrestricted route lengths and restricted max route length problems respectively. Following this a platooning model is generated and tested on various datasets, including a real-life example along the roads of the South East of the UK. Platooning proves to bring benefits to the VRP, with the extensions discussed in this thesis providing increased savings to emissions. On three of the dataset problems of the small and medium size problems a significant fuel saving of more than 1% was achieved. With future research and additional avenues explored Platooning can make a significant reduction to emissions and make an impact on improving air quality. The EV model proposed is designed to trigger further research on ultra-realistic energy models with the aim of being applied to a real-life organisation with various constraints including factors such as battery health, travel speed, vehicle load and transportation distance. This thesis provides useful insights into how important the aspect of environmental route planning is, providing advice on tangible and intangible benefits such as cost savings and a reduction in carbon emissions.

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This section is dedicated to a number of people who have helped me both directly and indirectly to achieve my goal.

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Chapter 1

Introduction

This introductory chapter aims at providing the reader with an insight into the green logistics area. A brief introduction to the current environmental impacts of transport and the current/future regulations employed to combat emissions are provided. Following this an introduction to the Vehicle Routing Problem (VRP) is presented, this popular management science topic is well studied within research, however it must be understood well in order to fully comprehend the advanced techniques applied within this thesis to reduce emissions and increase overall efficiency.

1.1 Green Logistics

Green Logistics is becoming increasingly important in today's society and gaining a higher level of awareness throughout the logistics and supply chain management area. In the UK the road transport sector was responsible for around 21 percent of UK greenhouse gas emissions in 2013, almost entirely through carbon dioxide emissions (Final Emissions statistics 2013, 2015). This topic is aimed at identifying aspects within the supply chain network that results in benefitting the environment and looks at improving the environmental sustainability of logistics. Green logistics highlights challenges that arise from such alterations and also provides advantages to thinking 'green' for both organisations and logisticians with the intention of encouraging all participants to consider the environmental impact of their processes and actions. The main objective of logistics is to provide logistical activities meeting customer requirements while minimising costs. In the past, cost has solely been defined in monetary terms. Green Logistics looks at changing this, highlighting external as well as internal costs. These external costs include climate change, air pollution, noise pollution, traffic pollution as well as accidents. A truly efficient green system studies ways in which these external costs can be reduced achieving a balance between economic, environmental and social objectives. In recent years there has been an increasing concern about the impact of these emissions and whether or not current logistic practises may be sustainable in the long term (Sbihi and Eglese, 2007). The importance of environmental issues are being translated into an increasing number of regulations which have a direct effect on the supply chain network, examples of such regulations can be found from the *European Commission Transport Sector*. As a result there has been an increase in research between logistics and environmental factors (Jabali et al. 2012). Transport organisations are having to increase their awareness of potential impacts both internally and externally, for all of their activities and services as they grow and develop. Individual Governments are bringing in increasing regulations to regulate the amount of emissions that are generated by organisations. The 2008 climate change act established the world's first legally binding climate change target. The UK government aims to reduce the UK's greenhouse gas emissions by 80% by the year 2050 from the baseline in the year 1990 (Government Policy 2010 to 2015). Scotland have committed to reducing their emissions to net-zero by the year 2045, 5 years ahead of the UK's governments target (BBC News, 2019). The UK's policy requires a drastic reduction in emissions and as the road transport industry are the main contributors to these emissions then it should be here where attention is focused, as can be seen in figure 1.1.1 where the dominant energy use category is transport. The total energy consumption of all transport modes in the EU-28 accounted for 1,065 million tonnes of CO_2 equivalents (Greenhouse Gas Emission Statistics, 2018). By-products from this amount of energy consumption in the transport sector include huge amounts of CO_2 and other pollutants that have a direct effect on global warming (Unger, 2009). Heavy duty vehicles (HDVs) are a significant contributor to these greenhouse gas emissions with around 16% of the CO_2 pollution in Europe (Road Freight Transport Vademecum, 2009).

Global efforts to reduce their emissions should be a priority as they can provide an immediate benefit and help avoid the dangerous tipping points in the climate system over the next few decades.

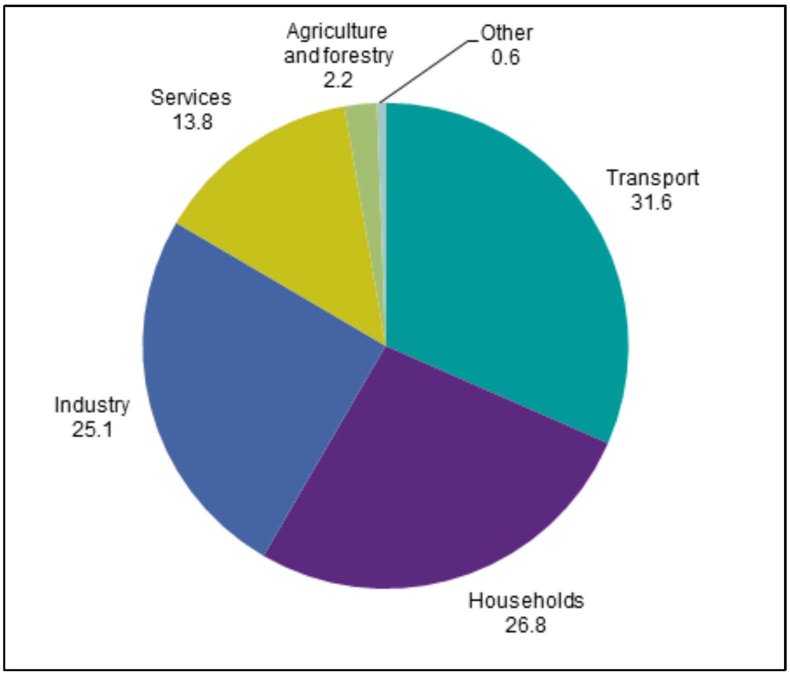


Figure 1.1.1 The final use of energy in the EU-28 in 2013, three dominant categories with Transport being the main contributor at 31.6% (European Environmental Agency 2015).

The latest UK government figures on transport provide a good notion of where the UK are heading and the current trends. Within the UK the most popular form of transport is road, in the year 2016, 78% of the UK population transport distance travelled was car/van based. However, its not just the public 76% of goods were transported via road transport, goods vehicles travelled a total of 19.2 billion km's, an increase of 5% from 2015. This not only generates increased emissions but also more traffic congestion and can have large effects on the road infrastructure of towns and cities. The trend for newer more efficient vehicles is pleasing to see, with 42,000 ultra low emissions vehicles registered in the year 2016, an increase of 40% from 2015 (Transport Statistics, Great Britain, 2017). Recent greener decisions made by the UK government include large investments in greener fuels such as biofuels, government monetary grants for Electric Vehicles (EV's) and accompanying Plug-in schemes as well as deciding to maintain with the European Union's carbon emissions goals, even after the EU removal is completed (Road vehicles: Improving air quality and safety, 2018). With tighter emissions regulations, and improved technology the UK are moving forward quickly with the adoption of greener transport, but is it quick enough. Chapter 6 delves into the UK Emissions and plans in more detail along with some analysis.

Environmental management systems (EMS) are being implemented to try and control, monitor and improve environmental impacts. Much work has been done to see how well these systems are used in an organisation and their impacts, examples include: Dillon and Fisher (1992), Melnyk et al. (2003), Chan E (2011), Lo et al. (2012). However, with CO2 emissions remaining stagnant these EMS' need to be revisited and improved. For Heavy Goods Vehicles (HGVs – vehicles with mass over 3.5 tonnes) fuel equates to around 30% of total operating costs in transport companies (Kolbl, 2012). This means using less fuel is not only better for the environment due to a reduction in emissions but also good business practise. Companies are devoting a lot of resources to the development of their environmental awareness. A common practise is Eco driver training; Driver training courses teach special techniques that not only help drivers keep safe, but also can reduce their fuel costs and environmental impact. Performance monitoring systems can also relay direct driver feedback to the driver and their supervisors allowing further improvement to economical driving. Combining eco driver training and performance monitoring systems can lead to further carbon reduction (Freight Carbon Review, 2010-2015). Recent improvement in technology is allowing electric vehicles to become progressively viable for businesses. Battery technology including design, materials, cooling and manufacturing processes has increased rapidly over the last 10 years with public electric vehicles in production now being able to travel up to 300 miles on a single charge (Jaguar I-Pace, 2018). The reduction in direct tailpipe emissions can help reduce the current emissions caused by the transport industry and will be a necessary investment looking towards the future. EV's can be considered under the branch of Alternative Fuel Powered Vehicles (AFV's) these are vehicles that are powered by fuel other than Petrol or Diesel. Within this thesis considerable focus is placed on EV's however for completeness for the reader other popular AFV's can also include Liquid Propane Gas (LPG) powered vehicles as well as, although less common, Hydrogen Fuel cell powered vehicles. In order for transport systems to be effective for users, efficient algorithms are needed. Algorithms reducing the emissions while also minimising the costs are becoming increasingly desired; it is hoped that the models developed in this thesis will provide many real-world benefits to companies within the transport industry and increase the awareness of emission-based vehicle routing problems.

1.2 Vehicle Routing Problem

The Vehicle Routing Problem (or VRP) is a very well-known combinatorial problem that is popular among researchers due to its many variants and its scope for development. The VRP is derived from the Travelling Salesman Problem (TSP). The aim of a TSP is to find the shortest possible route starting at one location, passing through every other location and returning to the same starting location. The VRP is a further extension of the TSP however it includes multiple routes/vehicles each of which can be considered to have its own TSP to solve. Typically concerning a delivery company, the VRP creates a set of routes that must start and finish at the depot, such that all customers' requirements are fulfilled within the given operational constraints.

The road network is described as a graph where the arcs are the routes traversed between customers and the nodes are the customers. Each arc has an associated cost, generally considered its length or travel time.

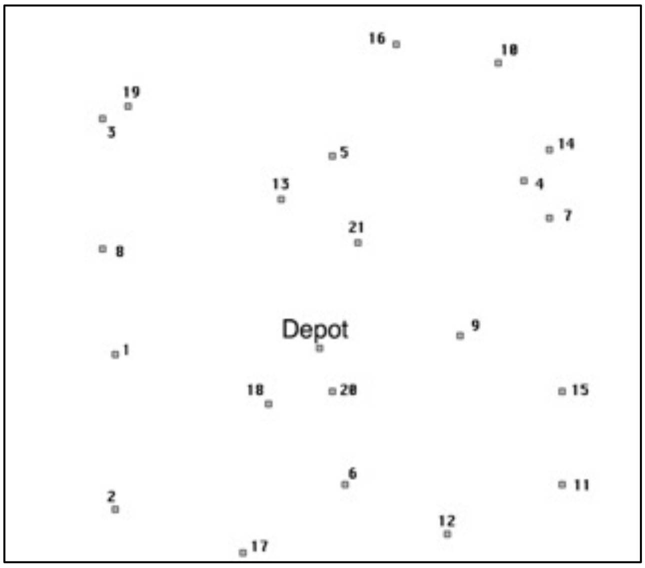


Figure 1.2.a Customers to be served from a central Depot

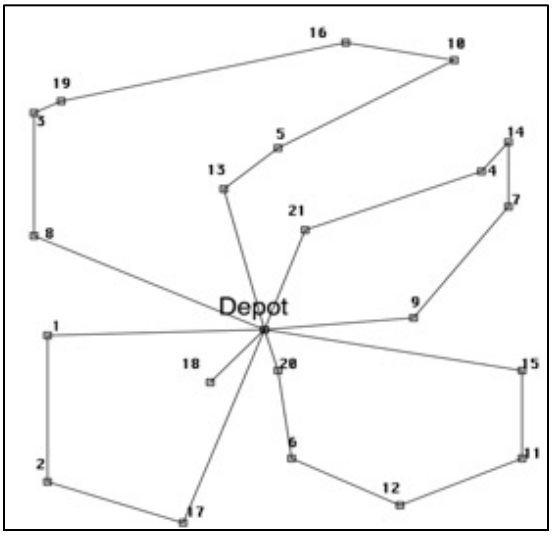


Figure 1.2.b Initial Solution with 5 vehicles

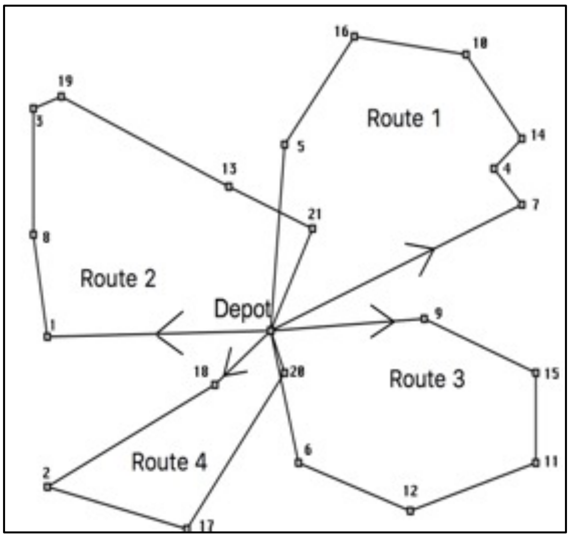


Figure 1.2.c Optimised Solution, with 4 optimal vehicles

The aim is to minimise the total distance of all the routes. Figure 1.2a shows the customers that need to be served by vehicles leaving from a depot, in this instance the depot is situated in the centre of the graph. Figure 1.2b provides a solution to the problem with 5 vehicles serving all the customers and returning to the depot. Upon inspection one of the vehicles can be seen to only serve 1 customer on their route. This is in most cases inefficient, and fleet operators may not be inclined to add another vehicle to their fleet to fulfil a single order due to expenses. Figure 1.2c further optimises the solution with a lower overall distance while using just 4 vehicles. Using computer methods to solves such problems as the VRP in a business situation can often lead to important cost savings, in many cases mean 20% of the total cost of the product (Toth and Vigo 2002).

Researchers in the subject area investigate the problem (and its variants) and often apply new or existing optimisation algorithms in order to solve this NP-hard problem. The VRP and all its variants share a common aim, that is, the production of a set of vehicle routes starting and ending at the depot/depots in a way so that all customers are served. A series of constraints follow these aims and vary in complexity and are often included to provide real world applicability to the problem. These constraints are often responsible for how variants differentiate. Examples of such constraints include a vehicles capacity, the number of vehicles available, the type of vehicles available, time constraints, a maximum distance that normal and alternatively fuel powered vehicles can travel, and loading constraints, further constraints will be highlighted within the literature review chapter. As the customer size of the VRP grows the problem increases in difficulty exponentially, combined with ever increasing complicated constraints further complexity is added into the models. Common objectives within the VRP include minimising total distance travelled, minimising the number of vehicles, reducing waiting times and more recently, reducing emissions. Part of this thesis focuses on the objective to reduce the emissions, while many models are considered green as they attempt and reduce the distance travelled, which is directly related to fuel, other factors need to be considered which are often not measured and frequently overlooked.

The vehicle routing problem is a complicated problem to solve when more constraints and variables are added, they are classed as NP-hard problems. NP-hard problems also known as

Non-Deterministic Polynomial-time hard problems, and they are not limited to decision problems. They can be defined as: a problem x is NP-hard if there is an NP-complete problem y, such that y is reducible to x in polynomial time. When trying to solve combinatorial problems such as the vehicle routing problem that is NP-hard typically two methods are used.

1) The first method that was used is an exact method. Exact algorithms as the name suggests compute every possible solution until the optimum is found. Every NP-hard problem can be solved by exhaustive search. However, when the number of instances increase, and the complexity rises the running time soon becomes too large to compute. Solving NP-hard problems to optimality is an area of research that has challenged researchers for generations. Exact methods have been studied and developed since the beginning of computing history. Due to the complexity of problems arising nowadays exact approaches are often limited to fairly small instances. Due to the complexity of the VRP only small instances can be solved optimally consistently.

A Survey conducted by Laporte and Norbert (1987) was the first work to show a comprehensive overview on the exact algorithms for VRPs. They classified them into three categories: direct tree search methods, dynamic programming and integer linear programming. Since then other algorithms such as the Branch-and-Cut-and-Price successfully combine methods to provide fast efficient results. The best-known exact algorithms for the symmetric CVRP can be classified into the following categories: Branch-and-Bound, Branch-and-Cut, dynamic programming and Set Partitioning (SP) based methods (Baldacci R, Mingozzi A, 2006). Several other key review papers were devoted to the analysis of exact algorithm methods including: Laporte (1992), Toth and Vigo (1998), Bramel and Simichi-Levi (1998), Naddef and Rinaldi (2002), Cordeau et al. (2002), Baldacci (2004), Toth and Vigo (2002).

2) The second method that is used is heuristics. Heuristic methods are growing in importance. They are becoming essential for decision analysts, managers and OR (Operational Research) practitioners' everywhere. All over the world an increasing number of companies are developing new technologies and products, they are striving to compete within this fast-developing market. As a consequence, there is a need to develop fast efficient problem-solving methods. When trying to solve a medium to complex problem exact solution methods often become impractical and very inefficient. Heuristic's provides the answer, a practical solution in a sensible amount of time. In the business world, time is money, a practical solution in a short time frame will in most cases be much more functional. F. Glover et al (2008) shows how ineffective and wasteful the exact method is when applied to the controlled tabular adjustment method. Real-life combinatorial optimisation problems are typically large in size and since exact approaches are insufficient, heuristics are implemented instead. Heuristics are immensely important when trying to solve large problems, they are viable in numerous areas. Heuristics provide idealistic near optimal solutions to many companies' problems, increasing profits, reducing risks and minimising waste. The increase in technology has meant more complex problems hence improved methods are being created which bought about the introduction of meta-heuristics. Today we see Optimisation problems everywhere and the list of applications seems endless; in order to solve these problems, we turn to heuristics. They are an important part of life and will become more so in the future, as problems grow in complexity.

Heuristic and Metaheuristic Algorithms to solve the VRP are constantly developed with many different techniques. Some of the most popular are in a group called constructive heuristics, these are methods that start with an empty solution and perform iterative steps until a full solution is produced. Methods include: Savings Algorithms, Insertion Heuristics and Cluster-Route (route first, cluster second and cluster first route second). Another popular class of heuristics is the local improvement heuristic. The method works by searching the neighbourhood space and uses iterative steps applying defined moves improving the solution until an optimum is reached. These heuristic methods will be described in further detail in the next section. Metaheuristics are also commonly used to solve the VRP seeking to speed up traditional time-consuming techniques. Various Metaheuristic algorithms are used within literature and often prove to provide good results, further detail can be found in the literature review section of this thesis. Another variant of heuristics that should be mentioned are Matheuristics, these combine heuristic methods with mathematical methods such as branching. While these are relatively new they show good accurate results, for this research these matheuristics methods are not used for further information the reader is directed to the book Matheuristics – Hybridizing Metaheuristics and Mathematical Programming (Maniezzo, Stützle and Voss 2010).

The VRP is essential to the transport industry and has been the backbone of many researcher's work, combining with the green aspects mentioned briefly, it is hoped that the combination can provide further real-world benefits. For the purpose of this research heuristic and metaheuristic methods will be used. Methods that are quicker to be implemented such as the Savings method will be used to get a good result in a reasonable amount of time. Once a baseline has been achieved further work on more advanced metaheuristic methods will be included such as VNS; this provides the structure for introducing fuel consumption reduction techniques such as Platooning as a post optimiser. The Platooning algorithm used within this thesis focuses on the initial customers and joins up two vehicles leaving from the depot. The vehicles travel towards the same point before splitting and continuing along their separate routes. Emission savings occur along the initial route travelled together, with multiple platoons being formed noticeable benefits in emission reductions can be achieved.

1.3 Motivation

In the current economy, markets are becoming increasingly competitive, none more so than the energy market. Investors are beginning to move from traditional fossil fuels to new forms of energy. Figures show the Royal Bank of Scotland has reduced its global lending to oil and gas companies by 70% in oil and gas firms in 2015 and doubled UK green energy loans to £1bn, according to new figures released to the Guardian. It has also recently been announced that institutions controlling $13 trillion of investor's money, are calling for G20 nations to ratify the Paris agreement last year and quicken investment in green technology and clean energy and forced disclosure of climate-related financial risk (Guardian, 2016). There is no doubt that green technology is the future, implementing such technology in a tangible way is becoming increasingly important. Efficient transport systems that are both environmentally friendly and cost saving are vital for success. Companies are constantly seeking to gain an advantage over their competitors, increases in environmental concerns from governments and the public (McCright et al. 2015) have meant that environmentally practises are now preferred. Advancements in technology has meant that vehicles have seen a reduction in emissions. Various techniques are used to reduce emissions by companies such as frequent renewal/updates of fleet vehicles providing 3 main benefits: firstly, more efficient engines producing less emissions. Secondly lower rolling resistances; when referring to vehicular transport these rolling resistances are primarily attributed to the force acting on a rolling tyre while the vehicle is in motion. Thirdly aerodynamic advancements resulting in a decrease in fuel consumption. Improving the aerodynamics of vehicles reduces the aerodynamic drag resulting in less force required to maintain a vehicles speed consequentially improving fuel consumption. Combined with adopting state of the art algorithms programs to efficiently manage their routing, companies can improve their efficiency and reduce overall costs while benefiting the environment.

One aim of this Thesis is to identify ways in which aerodynamic drag can be included and reduced using innovative techniques within the routing problem that can then be scaled into current logistics models/programs. With the most recent technology, complex vehicle monitoring systems have become powerful enough to provide safe driverless control to vehicles while travelling on public roads. Driverless technology removes human error when braking and accelerating that is caused from human reaction times. Using this system, a vehicle can safely travel behind one another in a close enough proximity so that the aerodynamic drag of the vehicles is reduced. This technique when used within transport is called Platooning and essentially describes vehicles that actively draft each other on the road. Platooning is being trialled within Singapore with the port operator PSA becoming the test bed for Scania's autonomous truck platooning system. Platooning of vehicles is largely affected by the speed and the distance between the vehicles that are drafting. However, fuel saving benefits of 7%+ can be seen from just two truck platooning, and a 4% benefit when factoring in real world conditions such as traffic (*Peloton*). Other programs such as the PATH (2004) program based in California estimates that fuel saving benefits of up to 20% can be achieved (Davila and Nombela 2013). With the possibility of large improvements in fuel consumption Platooning is a viable and worthy option within logistics. Methods for communicating within the platooning of vehicles have been studied within literature, with several applications being tested. For fairly recent implementations see CHAUFFEUR (2004), Energy ITS (2013), KONVOI (2009), PATH (2004), Scoop (2012), or SARTRE (2010).

The advancement in engine technology has helped greatly towards the progress the transport industry has been making in terms of carbon reduction over the recent years. However, arguably the fastest developing technology is that of Alternative Fuel Powered Vehicles. Electric delivery vehicles are the new trend with large companies in the USA such as Fed Ex and UPS (Anagnostopoulou Afroditi et al. 2014), with many top companies combining with manufactures designing their own (Workhorse Group 2017). Electric driving is a promising alternative to conventional fuel powered vehicles. They produce zero tail pipe emissions, with only brake and tyre wear. Although they can cause GHG emissions and other pollutants depending on the mix of electricity that is used to generate the energy that powers the vehicles batteries. Electric driving comes in a range of alternatives for the consumer. The first is the Plug-in Hybrid Electric Vehicle (PHEV) which typically has a small battery for trips up to 30 miles and an ICE to provide power for longer range driving. These can be charged from regular and dedicated power outlets. The second is an Extended-range electric vehicle (E-REV), which are much like the PHEV in terms of both having an electric and ICE engine however they differ by the electric motor in the E-REV always driving the wheels while the ICE is used to supply power to the battery when it is depleted. The third is the Battery Electric Vehicle (BEV) and are considered traditional electric vehicles where it relies entirely on electricity for fuel produced from the motor powered by the on-board battery, they typically currently range from an 80 - 300 mile range. The fourth is a series-parallel hybrid car (commonly referred to as just a Hybrid) whereby the ICE and electric motor are both connected to the wheels. The batteries charge is maintained by the ICE and it cannot be charged by plugging into a power outlet. These hybrids can travel very short distances on electrical energy. Other forms of electric driving such as fuel cell technology is discussed further in Chapter 5. The electric vehicles are increasing in popularity and are becoming a real viable alternative to the traditional ICE vehicle. As such the market has seen a huge uptake in Ultra low emission vehicles, they offer many benefits over the traditional vehicle such as: No fuel purchase needed resulting in them being cheaper to run, no direct emissions, Cost incentives, Low maintenance, reduced noise pollution and added benefits such as zero road tax and now the possibility of driving in bus lanes (BBC News 2016). However, they also bring with them some drawbacks which include: the number of recharge points and their accessibility, Short driving range, length recharge times, high cost of the batteries and battery degradation. While still in its infancy Electric Vehicle technology is on the rise and will prove to be of great significance in the coming years if we are to battle climate change. Providing up to date research based around the techniques and methods companies and organisations will be using going forward is of great significance and is the motivation of this thesis.

1.4 Aims and Objectives

This thesis aims to provide a new outlook on some existing models that are used within the vehicle routing problem in terms of both energy/fuel consumption and electric vehicle modelling, to provide inductive ways in which current variants of the vehicle routing problem can be considered green/environmentally friendly. Realistic additions will be made on state-of-the-art electric power consumption models which will aid in their accuracy with real life variants such as temperature, power generation variations, and gradients. A novel model introducing aerodynamic benefits known as Platooning is presented in a VRP highlighting the benefits of utilising this commodity and how it can be introduced into the research area reducing fuel consumption with the necessary literature reviewed. This Platooning model can be extended with various VRP methods and has the possibility to reduce the emissions considerably. Looking at the social, financial and ecological benefits it is evident that vehicle platooning will play a significant role when designing state of the art Intelligent Transport Systems (ITS) in the near future (Maiti et al. 2017). Solution methodologies are created and tested on the models to determine the accuracy and usability. The green logistics subject area is becoming increasingly more important, making this research more relevant and needed. Overall this thesis is hoped to trigger further research in the area and prompt researchers to look towards the future of technology today.

1.5 Outline of Thesis

The rest of this thesis is organised as follows:

Chapter 2 provides a general review on the VRP, also looking at the different variations and how they are framed with constraints and solutions, several newer problems are presented with useful references and insights that the reader will find useful. We review the recent literature around the Green vehicle routing area focusing on Platooning and Alternative Fuel Powered Vehicles (focussing on Electric Vehicles) as we feel these are very important aspects within the sustainability sector. This chapter also reviews solution methods used to solve these problems including Exact, Heuristic and Metaheuristic Algorithms.

Chapter 3 contains our basic model consisting of a VRP and introduces the basic Platooning model. This chapter provides the reader an insight into the algorithms in use and needed theory around platooning providing real-life applications. A heuristic and metaheuristic method model are created including VNS and other improvement heuristics to provide solutions to the VRP's tested. A CO_2 experiment is also conducted with valuable information for the research community. Results from the algorithms are provided as well as an analysis on the different techniques used. The Basic Platooning model is introduced and modelled. Results are provided alongside analysis.

Chapter 4 introduces advanced techniques to the platooning problem. We first look at reverse routing in order to improve our results generated from our VNS. The platoon pairing is enhanced using two distinctive techniques. Following this we investigate the platoon splitting point and introduce 2 more variants. We conclude with results and analysis for the advanced platooning techniques.

Chapter 5 provides a thorough overview of Electric powered Vehicles (EV's). A summary of the current transport emissions situation within the UK is provided including future plans and the real benefits/restrictions that EV's will play in our society. As well as a general EV model a Hyper Realistic Electric Vehicle Emissions Model is provided along with results.

Chapter 6 is the conclusion to the thesis, providing the reader with a conclusion followed by the impact and future research this thesis provides.

Chapter 2

Literature review

This chapter aims to provide the reader with a comprehensive background of the well-known and lesser-known variations of the Vehicle Routing Problem (VRP). Particular effort has been made to demonstrate how each variant can be considered to be environmentally beneficial. Additional emphasis is provided on those variants that we utilise within our models found in Chapter 3, ensuring that the reader has suitable knowledge when discussing the more advanced techniques within this thesis. The VRP provides the backbone to the research techniques carried out in this thesis, it is therefore important for the reader to gain a background in the problem. Following from the VRP literature is the Platooning literature, this is a relatively new research area as the required technology has only recently become viable. The Literature provides some key insights into the perspective research area, and the gaps within the literature are highlighted.

2.1 Vehicle Routing Problem Overview

The Vehicle Routing Problem has been approached by many researchers and as such now incorporates a wide range of variants. The VRP is an NP-hard and well-known combinatorial optimization problem. VRP is generic name that is given to a whole class of problems (Laporte et al. 1989, 2002). The general problem aims at optimizing a set of optimal routes used by a fleet of vehicles, based at one or more depots, to serve a set of customers. The studies can be separated into different variants and then also differ by providing mathematical formulations and exact or approximate heuristic solution methods for academic problems or case-orientated research papers. All variants stem from the original VRP proposed by Dantzig and Ramser (1959). The original classical case is closely linked to the VRP with time windows and the Capacitated VRP (CVRP). Most variants take into consideration capacitated constraints from the CVRP. The Green VRP can include Time Windows, Heterogeneous fleets, Electric Vehicles and numerous other factors. The Rich VRP's are the most data intensive problems and takes many different aspects into consideration as many variables can be used / need to be used to create real life instances. The principal objective of the typical VRP is to find the solution, where vehicle number is minimised together with the length of the total travelled path (Dantzig and Ramser (1959), Jih et al. (1996), Potvin and Bengio (1996), Tan et al. (2001), Jih and Hsu (2004), Alvarenga et al. (2005), Yeun et al. (2008)). Many of the VRP variants follow the same basic mathematical model, however contain different constraints that make them applicable to a variety of problems both real-life and simulated. The following sections within this chapter will discuss in more detail these variants and review the literature. The first section will discuss the very first variant to be discovered, the Capacitated Vehicle Routing Problem, which is also known as the classical VRP, this will then be followed with literature of its variants.

2.1.1 Classical Vehicle Routing Problem

The classical VRP was first discovered in 1959 by Dantzig and Ramser (1959) in the "The Truck Dispatching Problem". Like most problems that have risen in management science the problem was identified by a real-world problem. The formulation aims at optimizing a set of optimal routes used by a fleet of vehicles, based at one or more depots, to serve a set of customers. In addition, customers must be visited exactly once, and the total customer demand must not exceed the vehicles capacity (Clarke and Wright (1964), Laporte et al. (2002), Novoa et al. (2006)). Dantzig and Ramser (1959) refer to the problem as a generalisation on the Travelling–Salesman Problem (TSP) with the objective of designing an optimum route for a fleet of gasoline delivery trucks between a delivery terminal and service stations. Due to the nature of the problem this case is considered to be also classified as the Capacitated Vehicle Routing Problem as the vehicles are limited to a certain capacity. The VRP is represented in a graph theory. The general model case can be defined as the following:

> Let $G = (v, A)$ be an symmetric graph where $v = \{0,1, \ldots\ldots, n)$ is a set of vertices that represent locations/cities with a depot located at vertex 0, and other nodes $i > 0$ represent a customer and the arc set $A = \{(i\,, j): i\,, j\} \in v, i \neq j\}$. A fleet of m identical vehicles of capacity q is based at the depot. The fleet size is given a priori or is a decision variable. Each customer i has a nonnegative demand d_i. A cost matrix cij is defined on A. For simplicity, we consider travel costs, distances and travel times to be equivalent. The VRP consists of designing m vehicle routes such that each route starts and ends at the depot, each customer is visited exactly once by a single vehicle, the total demand of a route does not exceed q, and the total length of a route does not exceed a pre-set limit L. In the symmetric case, i.e., when $cij = cji$ for all $(i\,, j) \in A$, it is customary to work with an edge set $E = \{(i\,, j): i\,, j \in V,\ i < j\}$. c_{ij} can often be interpreted as the travel cost or time (Laporte (1992), (2009), Cordeau et al. (2010), Golden et al. (2008), Wouter (2008), Li et al. (2010)).

The classical VRP consists of designing a set of at most k delivery routes such that each route starts and ends at the depot, each customer is visited exactly once by exactly one vehicle, the total demand of each route cannot exceed the vehicle capacity and the total running cost is minimised. Stewart and Golden (1983) produce a compact formulation that includes the assumptions made prior and can be written as:

$$Minimise = \sum_{k=1}^{n} c_{ij} x_{ij}^{k} \tag{1}$$

Subject to

$$\sum_{i,j}^{n} q_i x_{ij}^k \leq Q, k = 1,2, \dots n, \qquad (2)$$

Where

c_{ij} = The cost/ distance of travelling from node i to j

x_{ij}^k = 1 if vehicle k travels from node i to j; 0 otherwise

n = The number of vehicles available

q_i = The amount demanded to location i

Q = The vehicle capacity

Usually the VRP is treated as symmetric meaning, $c_{ij} = c_{ji}$ (In the real world this is often not the case) and so the cost matrix is symmetric and needs to be calculated from geographical data by shortest path algorithms. Various methods can be incorporated to speed up the shortest path problems, these can be found later in this chapter.

The first paper containing the phrase "vehicle routing" in its title was Golden, Magnanti and Nguyan (1972). This name has come to be the generic term used for these combinatorial type problems. In the literature, many surveys have been presented analysing published works on the classical version of the VRP (Bodin, (1975), Bodin and Golden, (1981), Desrochers et al., (1990), Eksioglu et al., (2009), Laporte, (1992), Liong et al., (2008) and Maffioli, (2002)). The classical CVRP has been extensively researched over the last few decades, and as such the model formulation has been simplified and further developed. The basic capacitated vehicle routing problem (CVRP) is now described as the following: A single depot that serves a set number of customers with a fleet of homogenous vehicles with a finite capacity Q. The customers have known demands and locations that must be satisfied by the depot. Each vehicle must begin and end at the depot, with the total customer demand not exceeding capacity Q. The main objective for this model is to minimise the total cost of the tours, (the total distance travelled by the vehicles). There have been several studies in the literature that identify/survey the literature of

CVRP's (Baldacci et al., (2010), Cordeau et al., (2007), Gendreau et al., (2002), Laporte and Nobert, (1987), Laporte and Semet, (2002) and Toth and Vigo, (2002)).

2.1.2 VRP Variants

The following section will review the literature of several variants of the VRP. Within the VRP research area there are many different variants, a brief overview of the core variants is provided with more detail provided on the variants that will be included within the models found in Chapters 3 and 4.

2.1.2.1 VRP with Loading Constraint

This variation of the capacitated vehicle routing problem is often seen in literature due to its close ties with reality, is the 3D/2D loading constraint VRP. The 2D constraint problem is required to allocate a set of rectangular/square items to larger standardised rectangular stock units, with the aim of minimising waste. Most of the contributions from literature are focused on a case where the items packed have a fixed orientation in respect to the stock units (Lodi et al., (2002)). Dyckhoff et al. (1997) provide a comprehensive bibliography for the 2D Strip Packing Problem, where each item returns a profit and the objective is to maximise the return in profit. Both problems can be combined with the VRP to provide a viable model for logistics companies for real-life situations. The first attempt at a 2D packing problem model was made by Gilmore and Gomory (1961). The model designed uses column generation based on enumeration for all items that can be packed into a single bin. The basic model is as follows:

> A set of n rectangular items $j \in J = \{1,2, \dots, n\}$, each defined by a width w_j and height h_j. We are given an unlimited number of identical rectangular bins of width W and height H. W-edges must be parallel to the W-edge of the bins.

Let A_j be a binary column vector of n elements a_{ij} $(i = 1, \dots, n)$ equalling the value of 1 if the item belongs to the jth pattern, and 0 otherwise. The feasible solutions are then represented by matrix A, containing all possible A_j columns $(j = 1, \dots, M)$.

$$Minimise = \sum_{j=1}^{M} x_j \tag{3}$$

Subject to

$$\sum_{j=1}^{M} a_{ij}x_j = 1, \qquad i = 1,2, \dots n, \tag{4}$$

$$x_j \in \{0,1\}, \quad j = 1,2, \dots n,$$

Where

x_j = 1 if pattern j belongs to solution; 0 otherwise

A_j Columns satisfy $\sum_{i=1}^{n} a_{ij}h_i \leq H$

When combined with the VRP, conditions such as no items overlapping, items must be completely contained within the loading surface and sequential loading where when unloading an item, no item of any later delivery may lay in the way. The overall solution is generated when a Routing Plan and a Packing Plan are feasible. Many more models with exact and approximate solution methods are within literature the reader is directed to Pollaris et al. (2014) for a more detailed literature review.

The 3D loading constraint problem was first integrated into the capacitated routing problem in 2006 by Gendreau et al (2006) and was abbreviated to the 3L-CVRP. The 3L-CVRP has the advantage of being very relevant to organisations, as it can incorporate some key constraints e.g the loading of fragile goods. The placement of a box is given by a set of 3-dimensional coordinates of the corner of the box that is closest to the origin of the coordinate system. In addition, an orientation index indicates which of the possible spatial coordinates is selected. The following packaging constraints are involved, taken from Bortfeldt (2012):

Unloading sequence constraint. When customer i is visited it must be possible to unload all their boxes using movements parallel to the longitudinal axis of the loading space. No box demanded by a customer served after customer i must be placed between that of customer i and the rear of the vehicle.

- Weight constraint. Each box has a positive weight and the total weight cannot exceed the maximum load of the vehicle.

- Orientation constraint. The orientation is fixed with respect to height, 90° rotations are allowed.

- Support constraint. If a box is not placed on the floor, a certain percentage of its base area must be placed on top by other boxes.

- Stacking constraint. A fragility value is assigned to each box, if a box is fragile only other fragile boxes may be placed on top, whereas both fragile and non-fragile boxes may be placed on top of non-fragile ones.

The routing with 3D loading constraint problem was first developed by Gendreau et al. (2006) and has progressed from the classical VRP and traditional cutting and packing problems. The reader is directed to Wascher et al (2007) for a review on cutting and packing problems, identifying recent advancements in the area. Due to the nature of the problem being NP-hard, heuristics are often used for medium to large sized problems. Iori and Martello (2010) survey the state-of-the-art problems within the field of routing with loading constraints. Within the literature the majority of methods include hybrid metaheuristics, where the problem is divided into routing and packing. Tarantilis et al (2009) developed a hybrid heuristic model combining

Tabu search with guided local search. Bortfeldt (2012) also developed a hybrid algorithm combining the Tabu search for routing the vehicles with a tree search algorithm for loading the various boxes into the vehicle. Gendreau et al. (2006) propose a two stage Tabu search algorithm, where each stage is used to develop the routing and packing problem individually. Zachariadis et al. (2009) and Fuellerer et al. (2010) further study the packing problem. The loading problem has not been extensively covered within the green routing problem.

Proper packing techniques have important effects on total emissions produced. Practitioners often try and optimise their loads so that they are as full as possible, poor planning can lead to extra vehicles being used that if correctly planned wouldn't necessarily be needed leading to increased emissions. Load has a large effect on the fuel consumption/energy of a vehicle, the calculated amount is explained later in a detailed model. For a vehicle's journey while the vehicle is nearer full capacity i.e a heavier load, it is advisable that closer stops take place. This limits the distance the vehicle is travelling with a heavy load. Vice versa while the vehicle has a lighter load the longer stops between customer drop offs are preferred; this can have a significant implication on routing decisions. Figure 2.1.1. provides an example of how load can come into play within routing, in this example each customer demands the same amount of product i.e the vehicle leaves with 3 units and returns with 0 in each case.

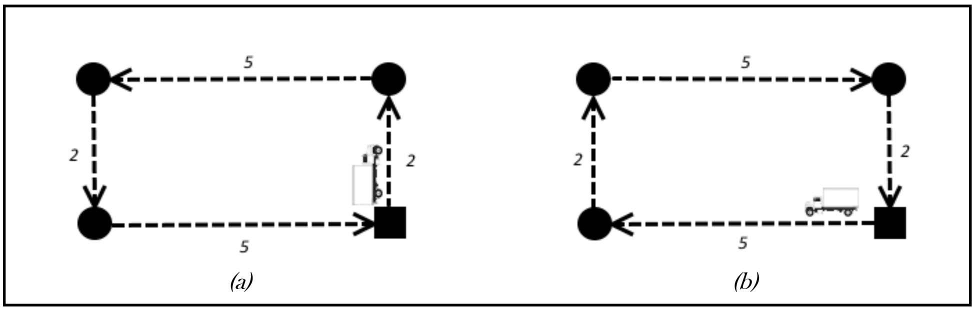


Figure 2.1.1 Simple routing diagram demonstrating importance of load on fuel consumption.

When looking at just route distance each route provides the same result, however when including load as a factor for fuel economy the first route *(a)* in figure 2.1.1 is preferred. The shorter arc distances are travelled when the vehicle is at its heaviest (i.e consuming the highest amount of fuel) leaving the longer arcs with a lighter load (i.e consuming less fuel for a longer distance). The result will be a significant reduction in route emissions.

2.1.2.2 VRP with Time Constraints

The vehicle routing problem with time windows (VRPTW) is a significant problem in the supply chain for logistics-based companies and as such, has been widely studied in the literature, mainly due to its relation to real life logistic problems (Zhang and Peng, (2012)). The routes must be designed in such a way that each point is visited only once by exactly one vehicle within a given time interval (time windows). All the routes start and end at the depot, and the total demand for all the points on one particular route must not exceed the capacity of the vehicle (Solomon, 1987). The VRPTW belongs to a class of the NP-Hard combinatorial optimization problems (Lensta and Rinnooy Kan (1981)). Due to this, large instances of the problem are most suited to be solved by heuristics. The VRPTW is formulated the same as the basic model proposed in section 2.11 with extra constraints. It can be defined as the same way as the classical however includes an associated travel time t_{ij}. The travel time t_{ij} includes a service time at node i, vehicles are permitted to arrive before the time window and wait at no extra cost until service becomes possible, however cannot arrive after the latest time window. The objective in most papers is to find the minimum number of tours K^*, for a set of identical vehicles such that each node is reached within its time window and the accumulated service up to any node does not exceed the vehicle capacity Q. Secondary objectives often include minimising total distance travelled.

The VRPTW has many useful applications to the real world, examples include bank deliveries, industrial refuse collection, school bus routing and JIT (just in time) manufacturing (Braysy and Gendreau (2005)). The VRPTW has been subject to extensive research using both exact and heuristic methods. An early survey of solutions to the VRP with time windows

(VRPTW), pickup and deliveries and periodic VRP was conducted by Solomon and Desrosiers (1988). Exact methods can be found in Larsen (1999) and Cook and Rich (1999). Braysy and Gendreau (2005) review heuristic and metaheuristic techniques employed to tackle the VRPTW. More heuristic and meta-heuristic techniques have been proposed by Potvin and Rousseau (1995), Rochat and Taillard (1995) and Taillard et al. (1997). Gehring and Homberger (2002) designed a parallel tabu-search heuristic that is capable of solving large-scale instances. Moon et al. (2012) extend the VRPTW to VRPTW with overtime and outsourcing vehicles using a mixed integer programming model, along with genetic and a hybrid simulated annealing algorithms. The most common way to compare computational times within the VRPTW context is to use Soloman's (1987) benchmark dataset. These datasets consist of a central depot, vehicle capacity constraints and time windows for the delivery as well as a total time constraint. Other measurement criteria within the problem is solution quality.

Other Time dependant variants of the VRP include the Time dependant Vehicle Routing problem (TDVRP). It has a similar objective to that of the VRP, minimising costs (Hill and Benton 1992). However, in the TDVRP the travel costs depend on the time of day a route is carried out. Varying speed zones linked to time zones can create such a model. This however can also lead to the undesired passing effect where vehicles that departing later may surpass vehicles that started travelling earlier (Fleischmann et al. 2004; Nannicini et al. 2010). By applying a first in first out assumption (FIFO) surpassing is not allowed.

Soft Time windows can also be incorporated into the problem. Soft time windows have a degree of flexibility within them allowing deliveries/pickups to be visited before and after the earliest and latest time window bounds. Allowing Soft time windows can often lead to a significant reduction in distance travelled however often these relaxations come at the expense of appropriate penalties that reflect the effect of customer satisfaction (Calvete et al 2004). This often arises due to a limited number of vehicles that can be used, unlike many proposed algorithms, and is used as a measured variable within models. Many transport operators in the real-world face similar constraints such as a fixed fleet. Additional routes/stops using 'Over Time' is generally associated with cost saving and is rarely considered green. In real life instances the amount of time drivers can operate for is an important factor in route planning, these time deadlines can mean deliveries can be missed. This could lead to extra journeys needed to satisfy customer demand. However, with the use of 'Over Time' these extra journeys could be reduced leading to a reduction in GHG emissions. This aspect has yet to be researched in depth to the best of knowledge and could be included within green models.

2.1.2.3 VRP with Backhauling

The Vehicle routing problem with backhauls differs from the classical VRP with one key aspect, which is the fleet used can consider pick-ups after deliveries are made. Some versions of the VRPB allow all the deliveries to be made before any pickups on a route; no route is allowed with only backhaul customers and there may be restrictions on the number of vehicles available that must be utilised (Toth and Vigo (1997), Osman and Wassan (2002), Wassan (2007)). The VRPB has been extensively researched separately however many variations are being developed. It was first developed in 1985 by Golden et al., (1985). Toth and Vigo (1996) provided further developed the problem and subsequently created several datasets that can be used to test this variant of the VRP for benchmarking purposes. Toth and Vigo (1997) put forward exact method approaches based on ILP formulations for up to 100 customers.

Extended variants of the VRPB include: The VRP with mixed deliveries and pick-ups (VRPMD) (Deif and Bodin, (1984), Salhi and Nagy (1999), Nagy and Salhi (2005)) where deliveries and pickups can be made in any order of the customers on a route. The VRP with simultaneous deliveries and pick-ups (VRPSPD) (Min (1989), Nagy and Salhi, (2005)) where the deliveries and pick up demands can come from the same customer. Tutuncu (2010) provide a practical paper looking at a heterogeneous fleet VRP with backhauls extending Tailard's (1999) model (VRPHE) by reducing the number of vehicles per type and incorporating backhauls. Many classical heuristics and metaheuristics have been proposed as solution methods for the VRPB. Brandao (2006) develop a tabu search algorithm, and Wassan (2007) who developed a reactive tabu search enhanced by adaptive memory programming producing good quality results. Wang and Hong zhen (2015) base their routing problem with green logistics in mind. They look at simultaneous delivery and pick-up problem with managers in mind, where they should consider the positive distribution and the reverse recovery for the target of environmental protection carrying out the practise of green logistics. Waste Management is often dealt with using backhauling and is an ever-increasing issue. Many councils over the U.K have developed policies and have devoted resources to planning waste collection/removal. Governments in recent years, have been focusing on waste recycling and waste avoidance (A. Sbihi & W.Eglese (2009)). Green logistics includes various aspects of waste management concerned with the transport of waste such as handling hazardous waste and household waste collection. Hazardous waste must be handled in specific ways in order to reduce the risk to human health and the environment particularly in urban areas (K.G. Zografos, G, M. Vasilakis and G.M Giannouli (2000)). Retailers are gaining responsibilities relating to storage, collecting, treatment, disposal and transportation of materials and products that have reached their end-of-life and are now considered hazardous. In order to do this efficiently retailers and organisations must develop cost effective strategies in order to optimise the collection processes of hazardous waste.

The Fleet size and mix vehicle routing problem with backhauls (FSMVRPB) was developed by Salhi et al. (2013). FSMVRP's in literature differ in two main ways, whether or not the variable running cost per vehicle is constant and whether the number of available vehicles is known or not. This variant is a more realistic routing and distribution problem with a wide applicability for logistic based companies that want to determine their composition of vehicle fleet as well as managing their vehicle routes efficiently so to achieve a competition advantage. The hybrid tabu search and scatter search algorithm proposed performs very fast providing stability and effectiveness only limited by the initial solution quality.

Although rarely mentioned, Backhauling can play a pivotal role within the emission reduction routing systems. Backhauling can be an influencing factor due to practitioners utilising 1 vehicle to carry out multiple jobs of delivery and collecting. With fewer vehicles on the road emissions can be reduced, however the actual carbon emissions of choosing less vehicles with fuller capacities over more vehicles with less capacities. The term Reverse Logistics is often used within the industry to describe the process of moving goods from their typical final destination for the purpose of capturing value, or proper disposal. Remanufacturing and refurbishing activities also may be included in the definition of reverse logistics. Literature around reverse logistics routing started becoming a hot topic and draw attention among researchers in recent years from its introduction in 2001 by Cordeau et al (2001) and when it gained traction in 2006 (Lin et al, 2014). The majority of reverse logistics problems within the VRP deal with recycling waste or end-of-life goods to one or more depots for further reprocessing. Within reverse logistics literature for the VRP 4 distinctive classifications can be created. The selective pickups with pricing, Waste collection, End-of-life Goods Collection and Simultaneous Distribution and Collection or pickup and delivery. While not included within the model in this thesis, these 4 classifications of reverse logistics offer an important and interesting aspect of sustainability models and shouldn't be overlooked. For more information on how reverse logistics is implemented within the VRP the reader is directed to Wassan & Nagy (2014), Malladi & Sowlati (2018), with more general Reverse Logistics review provided by Govindan, Soleimani & Kannan (2015). Reverse logistics also leads onto several variations to the VRP, cross docking is a useful logistic practise used by many companies to reduce logistical costs.

2.1.2.4 Mixed Fleet VRP

Unlike the classical case for the vehicle routing problem the mix fleet incorporates a mix of vehicles with different characteristics that are considered when route planning. The VRP with heterogeneous fleet of vehicles HFVRP or mixed fleet MFVRP was first considered in a structured way in Golden et al. (1984). Case studies appear in Wu et al. (2005), Tavakkoli-Moghaddam et al. (2007) and Baldacci et al., (2007, 2008, 2010). In the problem the vehicle fleet is composed by m different vehicle types with $M = \{1,2, \dots, m\}$. For each type $k \in M, m_k$ vehicles are available at the depot, each having a capacity Q_k. Each vehicle is also associated to a fixed cost F_k, routing costs on arcs may be vehicle dependant, allowing it to be possible for different vehicles to have varying arc costs. For full model detail the reader is directed to Baldacci et al. (2008), here the researchers identified five major subclasses: if the number of vehicles available are limited or not, whether there is a fixed cost or not associated with the vehicles and if the routing cost is dependent on vehicle. Baldacci, Battara and Vigo (2007) provide an extensive survey on the Heterogeneous Fleet VRP covering the main results up till 2007.

Solution techniques vary with this problem most researchers prefer heuristic techniques with few exact approaches. Baldacci et al (2010) applied a general branch-and-cut-and-price technique to the fleet size and mix vehicle routing problem with time windows (FSMFTW) model. Exact methods for the FSMF (fleet size and mix CVRP with independent routing costs and fixed vehicle costs) and other variants such as FSMD (fleet size and mix CVRP with vehicle dependant routing costs) and FSMFD (The fleet size and mix CVRP with fixed vehicle costs) were proposed by Pessoa et al. (2007), However the exact algorithm proposed by Baldacci and Mingozzi (2009) outperforms that of Pessoa et al. (2007). Computational testing for the HFVRP is generally conducted using benchmark datasets from Golden et al. (1984) using 20 test instances, customer size ranges from 12-100.

In terms of emissions the mixed fleet allows for further optimisation of the routing problem. Vehicles differ in terms of emissions when constructed, while being operational, during servicing and at their end of life. For the most part only the operational and servicing emissions are relevant to logistic based companies although the other factors should not be neglected in research. Hiermann et al. (2016) investigate the Electric fleet size and mix vehicle routing problem including time windows and recharging stations. This model provides decisions to be made with regards to the fleet composition and the vehicle routes compromising of recharging times and locations as well. In the model the vehicles vary in their capacity, battery size and the acquisition cost. This model has real-world application as companies have a variety of available electric vehicles with differing characteristics (Austriatech, (2014)). Goeke and Schneider (2015) included load-dependant energy consumption within their rich fleet model using both conventional and electric vehicles. The authors include average speed, vehicle mass and gradients in terrain. The objective function was split into three different functions, first the total distance is minimised, second the overall energy cost and driver wages are minimised and finally the third extends the second objective by including battery lifetime cost. The model created does not include partial recharges or degradation of the batteries.

2.1.2.5 Real-life VRP

In recent years the development of technology has led to increasing attention to new variants involving more complex constraints and objectives. These are created through the complex constraints of real-life problems called Rich Vehicle Routing Problems (RVRP), and hence they are much more challenging than the CVRP (Hasle et al. (2006)). RVRP's can incorporate a number of other variants however have more real-life complex constraints. RVRP's can therefore be applicable for complex energy constraints found within electric vehicle routing. There are many tailored approaches, however in the last ten years the general-purpose methods are emerging retaining previous quality features but for generic Rich scenarios (Caceres-Cruz et al. 2014). These real-life constraints can be related to the following aspects:

- Customer: In the traditional VRP each customer has a demand however in more complicated problems customers' requirements may include, service time, service type (pick up/delivery) or a vehicle type. In certain situations, customers are allowed to be visited more than once by multiple vehicles. Customers can also store their goods and so in some cases the distributor needs a routing plan taking this into account. This route planning can be tailored to also reduce emissions.

- Depot: There can be multiple depots, and these depots may have different purposes to try and reduce the cost in the overall supply chain. This cost can be monetary or emission based.

- Vehicle: The fleet may be heterogeneous, with different capacities, driving ranges, emissions and fuel types. Real-life situations often have a limited number of vehicles that can be incorporated. In Multi Depot situations vehicles may have different bases.

- Drivers: The drivers have very strict regulations that they need to adhere to, working shifts and maximum driving stints. They may also be qualified to drive certain vehicles.

- Objective: Minimisation of the number of vehicles, balanced workloads for drivers, maximisation of the number of customers served in order to increase service level, Minimise energy consumption or emission production. These objectives can sometimes conflict with each other.

- Uncertainty: Uncertainties can occur when route planning for example, locations and demands for customers may be unknown at the beginning when the vehicles first left.

- Goods packing: 2D and 3D weighted items need to be packed in the correct layout for a feasible route.

From the aspects outlined above one can see the complexity of the problem, with large scale problems metaheuristics play a crucial role in solving these problems. Doerner and Schmid (2010) present a survey devoted to hybrid metaheuristics for RVRP's identifying potential areas of future research. Recent attempts have proposed unified models tackling different classes or routing problems (Ropke and Pisinger (2006), Subramanian et al. (2012), Derigs et al. (2013), and Vidal et al. (2013a),(2013b)). Hartl, Hasle and Janssens (2006), Hasle, Lokketangen and Martello, (2006) Published special issues on rich combinatorial optimisation problems with cover formulation and resolution for problems. For more information on the RVRP the reader is directed to Lahyani et al (2015), who create a taxonomy that builds a framework to classify RVRP's. Papers were used from 2006, considering real-life and academic works that have been used as benchmarks. RVRP's can help increase accuracy when developing routing algorithms for electric vehicles and emission calculations developed within the models. However, with electric vehicles being constrained by range and charging locations small fluctuations in energy consumption may hinder performance and vehicles may not be able to reach their predestined customer/location. The ability to be able to evolve these routes over time, dependant on the inputs, would be able to provide more options for the user and the drivers of the vehicles.

The Dynamic VRP (DVRP) is a variant where customers are revealed incrementally over time rather than being known beforehand (Psaraftis, (1995)). The DVRP allow companies and organizations the possibility of on-route planning in real-life. Dynamic problems can arise from applications where the information provided/received changes over time. An example of this would-be traffic updates. DVRP's also provide important energy information for range limited vehicles such as EV's. With limited range and charging times to take into account, delivering live feedback to routing systems could reduce unnecessary costs. DVRP's are popular in real world problems due to their ability to handle this extra data allowing businesses to manage fleet sizes and handle more jobs (Regnier-Coudert et al. (2016)). The Periodic VRP (PVRP) extends the classical VRP by extending planning period to m days rather than just the single day (Mourgaya and Vanderbeck, (2006)). The objective is to minimise the travel time needed to supply all customers.

Within the electric vehicle there is scope to include various real life/rich parameters. Charging at different times of the day can result in varying emissions. Currently this hasn't been investigated within the vehicle routing problem however has been look at in other areas of research. Jochem et al (2015) assess the CO_2 emissions of EV's in Germany for the year 2030 optimising controlled charging strategies. One of the assessment methods used in their research was Time-dependant average electricity mix. This time-dependant average mix takes into consideration how much energy is charged in a certain hour. This allows for much more resolution into the emissions generated via EV charging. EV loads peak during the evening's when people return from home, the corresponding power needed to meet the required electricity demand means that alternative power sources are needed. Often these are higher emission energy sources, typically within the UK this is coal power generation that is used only at peak hours; this is discussed in more detail in Chapter 2 Section 2. With direct access from the power grid information real-time, a far more detailed emission model can be created, although this will bring with it added complexity, it should be investigated within the routing problem. Amongst the literature around the Rich/Real-life VRP there are always assumptions made. While a true real-life model is desired to further enhance the model's accuracy, ultimately some assumptions are needed. The balance between these assumptions and model accuracy (which introduces increasing complexity and therefore computational power) is a fine line. With sustainability becoming more prominent, different emission factors are becoming more important. In an ideal model all these emissions factors should be included to produce a true emissions model which can then be disentangled.

2.1.2.6 Summary of VRP Variants

The VRP consist of a broad range of problem variants, the ones discussed within this literature review were chosen as they provide the reader with knowledge needed for the models created in this thesis and can also be used to improve sustainability. Load makes a large difference on fuel consumption and is therefore something that needs to be taken into consideration when creating a VRP model. The ability to calculate the fuel consumption at various points along a vehicles path can allow the model to optimise the paths to ensure the vehicles are travelling their longest trips with their least cargo. Time constraints are needed in VRP's in order to make them applicable to real-world problems. However, time constraints can also be employed to reduce emissions by having restrictions on heavy traffic zones, easing congestion and reducing stop/start scenarios and therefore reducing emissions. Backhauling models allow the same vehicle to carry out multiple jobs. With a cost and pollution savings achieved through less vehicles and better vehicle efficiency, Backhauling models should be utilised by their compatible companies more so. Mixed fleet models take into consideration different types vehicles with various loading capacities and efficiencies, with the motor industry developing at a fast pace the latest vehicles can provide a good fuel saving over previous generations. The cost for the latest technology is, however, more expensive, companies therefore are more likely to slowly change their fleets introducing hybrids and electric vehicles when possible. The utilisation of a mixed fleet model makes optimising routing these various types of vehicles possible. While many researchers still propose highly tailored solution methods, we believe the future direction should be towards multiple real-life characteristic problems that can provide real-world benefits. With EV's gaining traction and a big concern the limited range, live updates on energy levels and ranges could alleviate concerns providing options for recharging and alternative routes. Although a larger number of constraints will need to be used, the increase in accuracy is deemed valuable as it can help reduce emissions. Through reviewing the literature, we have been able to identify several gaps within the literature that allows the aspect of emission reduction to included. Data Analysis can be introduced within the models to provide more accurate constraints and variables, with the advancement of electric vehicles and the ability to generate data, providing live information into the models can provide further benefits and increase the power of these computational models.

2.1.3 Solution Methods for the VRP

The vehicle routing problem attracts much attention from researchers due to its usefulness in real-life for the logistics and transport industry and continues to draw attention. Many methods have been studied to solve the VRP, these methods can be separated into exact and heuristic methods.

2.1.3.1 Exact Algorithms

Exact Methods attempt to solve the problem to optimality using a range of algorithms. The best-known exact algorithms for the symmetric CVRP can be classified into the following categories: Branch-and-Bound, Branch-and-Cut, Dynamic Programming (DP) and Set Partitioning (SP) based methods (Baldacci R, Mingozzi A 2006). Although exact solutions provide optimal solutions their computational time is its downfall, often with large complex problems they struggle to solve in a reasonable time. Successful exact methods for the CVRP were proposed by Fukasawa et al. (2006), Baldacci et al. (2008) and Baldacci and Mingozzi (2009). While this is by no means an exhaustive list, it gives the reader an insight into some of the exact techniques used.

The effectiveness of branch–and–bound algorithms almost entirely depends on the quality of the lower bounds used to limit the search tree. More sophisticated bounds allowed a larger size of problem to be solved to optimality (Toth and Vigo 2002). Christofides, Mingozzi and Toth (1981) describe a Lagrangian bound based on the SP formulation where the columns correspond to the set of q-routes. A q-route is a simple cycle covering the depot and a subset of customers whose demand is equal to q. The formulation was used to solve problems up to 25 customers. Christofides, Mingozzi and Toth (1981) also present three dynamic programming formulations of the CVRP. The state space relaxation method is used for relaxing the dynamic programming recursions so that valid lower bounds on the value of the optimal solutions can be found. Fisher (1994), Miller (1995) and Martinhon et al. (2000) use the Lagrangian Relaxation which duplicates some of the relaxed constraints and adds them to the objective function. Strengthening the relaxation also improves lower bounds and is done by adding some valid inequalities which are satisfied by all feasible solutions, Baldacci et al. (2007) propose some inequalities. The Branch-and-Bound can be extended to Branch–and–cut methods. In the Branch-and-cut, the lower bound of each branch node is iteratively improved by adding valid inequalities violated by the current solution to the relaxed formulation. Successful methods capable of solving up to 135 customers have been generated by Baldacci et al. (2004) and Lysgaard et al. (2004). Baldacci et al. (2004) also describe a branch–and–cut algorithm based on a two–commodity network flow formulation of the CVRP. For a survey of branch–and–cut methods for the CVRP see Naddef and Rinaldi (2002). Balinski and Quandt (1964) introduced the SP formulation of the CVRP, where each column corresponds to a route in 1964. However, this formulation is not practical as it involves an exponential number of variables. Agarwal et al. (1989) proposed a column generation (CG) algorithm where column costs are given by a linear function over the customers yielding a lower bound on the actual route cost. Some of the best exact method currently available for the CVRP has been proposed by Fukasawa et al (2006). Their method combines the branch-and-cut of Lysgaard et al. (2004) with the SP approach with is interpreted as column generation. The columns correspond to the set of routes that strictly contains the set of valid CVRP routes. The lower bounds are improved compared to Lysgaard et al. (2004) and Fukasawa et al (2006) was able to solve previously unsolvable instances. For further surveys on exact methods the reader is directed to Toth and Vigo (2014).

2.1.3.2 Heuristic and Metaheuristic Algorithms

Heuristic evaluation is subject to a comparison of different criteria that relate to that algorithm's performance. The criteria include running time, solution quality, robustness, flexibility and ease of implementation (Cordeau et al. (2002)). Heuristic solution methods used to solve the VRP can be split into three categories, Constructive, Insertion and Local Search Heuristics. Constructive heuristics are typically used to solve the VRP and seek to create a full solution from empty iteratively. These heuristic methods aim to solve combinatorial problems to optimality/near optimality in a reasonable amount of time. The Savings Algorithm was originally proposed by Clark and Wright (1964) starts with an initial solution where every node or customer is visited by a separate route from a depot. The Algorithm then proceeds to search and merge two routes together maximising the saving cost, this cost is often taken to be distance. Merges continue until they are no longer feasibly possible. The method often yields a relatively good solution deviating from the optimal solution slightly.

Insertion heuristics are very popular among researchers from solving VRP's as well as TSP's and scheduling problems. These techniques were originally introduced for the TSP and belong to a route construction problem (Rosenkrantz et al., (1977)). The method begins by starting at a single node or customer that is usually referred to as the seed node, which forms the initial route from the depot. Nodes are then added one by one performing functions to select the next node and insert it into the route. There are various well-known insertion techniques used in TSP that categorise how the node section is inserted: Nearest Insertion, Random Insertion, Farthest Insertion and the Cheapest Insertion. With the Farthest and Nearest insertion each node is selected for insertion according to the distance from the already constructed route, minimisation and maximisation functions are then implemented respectively on a cost function $c(n_i, n_k, n_j)$. A cost function is used to evaluate the node inserted and is structured as: $c(n_i, n_k, n_j) = l(n_i, n_k) + l(n_k, n_j) - l(n_i, n_j)$, where n_i and n_j are the current inserted nodes and n_k is the node to be inserted, $l(n_i, n_j)$ is the distance function. The Random Insertion heuristic selects its next node by random from the remaining set of nodes not already in a route. The point where a randomly node is to be inserted in the route is determined by minimizing a certain cost function as above. Cheapest Insertion selects the node for insertion by minimizing the defined function for all nodes and all places on the route (Soloman, 1987). Soloman (1987) divides these algorithms into either sequential or parallel methods. Sequential methods aim to construct one route at a time until all the customers are used. Parallel procedures are characterised by the simultaneous construction of routes, either limited or able to be formed freely (Joubert, 2004). Often these insertion techniques are used as initial solutions for local search (LS) algorithms, the way these initial solutions are formed, and their effectiveness have a large effect on the overall performance of the LS heuristic.

The main principle of the local search (LS) improvement heuristics can be defined as follows. A move-generation mechanism generates neighbouring solutions by changing attributes of a given solution. Once a neighbouring solution is generated, it is compared against the current solution. If found to be better than the neighbouring solution replaces the current solution and the search continues. When the solution is accepted it can be split into different strategies (In VRPTW context), first-accept and best-accept (Braysy and Gendreau 2005). This search approach finds a local optimum and is called Hill Climbing (HC). It is a popular method used in other algorithms for improvement of solutions. Local searches work on improving initial solutions. Improvement heuristics can often get trapped within local optima and fail to find the global optimum. This is where heuristic searches are used to temporarily decrease the objective value allowing it to escape the local optimum and find a better solution, these can also be referred to as metaheuristics which are described in detail later. One example of a LS heuristic is the shift/swap/move method.

- Shift/Swap/Move. This method involves swapping a particular customer with another within different routes (inter-route). The swap can include various numbers of customers; the (1-1) swap allows for 1 customer to be swapped with another, the (2-1) move is where 2 customers are exchanged with 1 other customer. This process can also be used to insert customers from 1 route to another i.e. (1-0) shift, This technique will be covered in greater depth in Chapter 3.

The intra-route exchange is another local search improvement technique used to improve paths.

- *Intra-route*. This exchanges neighbourhoods within a single route in order to improve. It is defined to be a set of solutions obtainable by removing the path whose length is not at the start or end of the route and inserting it in a position not at the start or end of a route.

Another Example is the 2-opt local improvement approach (Croes 1958; Hertz et al., 1999; Vidal et al., 2013):

- *2-opt*. A neighbourhood contains a set of solutions that can be obtained by removing two edges in a solution and adding new ones to reconnect the route.

It tries to improve the tour by replacing two of its edges by two other edges and iterates until no further improvement is possible with n^2 possible exchanges. It was first proposed by Croes (1958) in order to solve the Travelling Salesman Problem. 3-opt increases the number of arcs that can be exchanged with n^3 possible exchanges.

The results from the 2-opt tend to be very good examples can be found in Savelsbergh (1992). In addition to the 2-opt method other local search methods exist examples are Shift, Or-opt, Cross exchange (Laporte et al., (1999); Cordeau et al., (2005); Vidal et al., (2013)). Local searches and heuristic approaches often produce a near optimal solution within a reasonable computation time. These methods may be sensitive to data sets given, this is also known as robustness, or require additional preparation on the data during the learning process.

Metaheuristics provide another approach for solving a complex problem that may be too difficult or time-consuming by traditional techniques. Metaheuristics use high level algorithmic approaches to search for feasible solutions and are popular among researchers. Some of the metaheuristics that are applied to the VRP's are the following:

- *Tabu search* (TS). The tabu search is proven to generate decent results from the VRP. It uses an aggressive guiding strategy that directs any local search to carry out further exploration of the solution space, avoiding being trapped in a local minima. If a local minima is found TS moves to the best location in the neighbourhood. To prevent a move in the search that was already performed during specified number of last iterations the TS uses memory structures. Restrictions are stored in memory called a tabu list (Wassan and Osman 2002). Tabu search can be seen as an extension of the classical local search heuristic, where a solution space is explored by repeatedly implementing moves to generate solutions within the neighbourhood of a previous solution. Within the VRP, two main Tabu neighbourhood structures can be defined. The first is referred to as λ-interchanges which allows exchanges up to λ customers two routes. The second is referred to as ejection chains, performs exchanges between more than two routes simultaneously. For more TS reading see (Cordeau et al., 2001; Brandao, 2004; Archetti et al., 2006; Yeun et al., 2008; Vidal et al., 2013).

- *Large neighbourhood search* (LNS). The large neighbourhood search heuristic belongs to the class of heuristics known as a very large scale neighbourhood search (VLSN) they have shown outstanding results in solving transport and scheduling problems (Pisinger and Ropke, 2009; Vidal et al., 2013). An initial solution is gradually improved by alternatively destroying and repairing the solution. The large neighbourhood search maintains two solutions: the best solution found and the current solution. If a current solution is found such that meets the acceptance criteria function, the best solution is replaced with the new solution. In *adaptive large neighbourhood search* (ALNS) several insertion and removal heuristics are applied the neighbourhoods are applied depending on their performance in previous iterations (Pisinger and Ropke, 2009). In *Variable neighbourhood search* (VNS) when a local minima is found, it proceeds to the next neighbourhood in the nested structure; whenever a best solution is found the search restarts from the first neighbourhood (Laporte 2007).

- *Variable neighbourhood search (VNS).* VNS is another neighbourhood search technique that is often applied to VRP's and their derivatives. The VNS algorithm shifts among different neighbourhood structures which define different search spaces. Different variants of the VNS are used within literature. The first is the basic VNS, here a local search procedure finds local optimal solutions using a variety of neighbourhood structures, once found a shaking procedure is used to perturb the search which in turn enhances diversification within the solution space. Variable Neighbourhood Decent (VND) is a variation of the VNS whereby the shaking/neighbourhood change is deterministic (Hansen and Mladenovic, 1998). Other variations include the reduced VNS, which moves randomly in between neighbourhood sets.

- *Ant colony optimization* (ACO). Is inspired by the behaviour and movement of the ants. Each ant moves randomly around the nest and when the food is found, the ant returns to the colony by laying down pheromone trails. When other ants find this path they go by that path with higher probability than going on a random path. Evaporation techniques lead to optimization of the path length. As on longer paths the pheromones will evaporate more than shorter ones because of time needed to travel down the path and back again (Rizzoli et al., 2007; Yeun et al., 2008; Jančauskas 2014; Vidal et al., 2013).

- *Genetic algorithm* (GA). Is a population based algorithm that follows evolution and natural selection, where the fittest survive. There are several approaches that are designed to solve specific VRPs. The basic concepts originated from Holland (1975). GA evolves a population of chromosomes (individuals) by creating offspring through an iterative process until a set criteria is met. These criteria can include maximum number of generations or getting to an optimal solution. Once the offspring are then created, they are compared to their parents if a better solution is found then the offspring is considered a new parent for the next iteration.

2.1.3.3 Summary of Solution Methods

The heuristic and metaheuristic methods described within this section all have their own advantages when it comes to solving the VRP. In general, the most powerful metaheuristic method employed within the VRP is the Tabu search due to its memory capability and more so its variants introducing mutation tactics in the improved Tabu search metaheuristic (Jia et al. 2013). Within this thesis we have chosen to employ fast and effective algorithms such as the VNS to provide a good quality solution that our platooning model can then work and improve from. For further reading on the effectiveness of meta-heuristic methods for the VRP the reader is directed to Prins (2004), Cordeau et al. (2005) Mester and Bräysy (2007), Pisinger and Ropke (2007), Kytöjoki et al. (2007), and Laporte (2007).

2.2 Alternative Fuel Vehicles

This section reviews the literature related to the Alternative Fuel Vehicle Routing Problem focusing on the Electric Vehicle Routing problem. An alternative fuel powered vehicle (AFV) encompasses vehicles which are not powered by traditional fuels such as petrol or diesel. AFV's can also include electric vehicles (EV's) as well as other variations of fuel including LPG. Green logistics contain a number of factors including not only speed, distance and load but also alternative fuels. When considering AFV's or specifically EV's issues such as recharging and refuelling need to be considered. Some organisations have converted part of their fleets to AFVs in order to help reduce emissions and satisfy governmental environmental regulations (ErdoÄŸan and Miller-Hooks, (2012)). Alternative fuel vehicles are becoming increasingly desirable while medium and heavy-duty Lorries comprise only 4% of the vehicles on the roadways (US FHWA, (2008)), they contribute nearly 19.2% of US transportation based GHG emissions (US DOT, 2010). Alternative fuels include: biodiesel, electricity, ethanol, hydrogen, methanol, natural gas (liquid-LNG or compressed-CNG) and propane (US DOE (2010)).

Most companies do not operate pure EV fleets and so mixed fleet algorithms are used (Schneider and Goeke, (2015)). While energy costs for operating EV's are generally lower, labour costs may increase due to increased fuelling/charging times. The large growth in the transport sector recently has made it a large influencer on GHG emissions. Governments are becoming increasingly aware of the urgency to tackle transport problems, preserving the environment. Investing in environmentally friendly modes of transport such as Electric Vehicles is becoming a popular viable, however, a good infrastructure needs to be in place in order to make it feasible. Planning of these electric infrastructures are becoming of increasing interest, making research of the Electric VRP more significant (He et al. (2013), Mak et al. (2013), Nie and Ghamami, (2013) and Wang and Lin, (2013)). The Electric Vehicle Routing Problem is a variation on the traditional VRP, using electric vehicles instead of conventional fuel powered, with limited driving ranges. Charging station location planning is key in the optimisation of Electric vehicle routing. Recently public interest in EV's has risen and the tipping point for mass EV uptake is upon us (James Murray (2016)). Nissan (leaders in mass market EV) believes that by end of the year 2020 the charging stations will outnumber petrol stations reaching 7900. Combined with the increase in battery technology mass EV uptake will be upon us soon (Edward Jones EV manager at Nissan Motor (GB Ltd)). This increase in infrastructure will reduce constraints on electric fuel stations within the routing problem and allow further benefits to be identified. However, with an increase in electric chargers can mean that if a company can gain a stronghold on charging points it can monopolise the market. Currently the main supplier for electric charging stations is Ecotricity with the most comprehensive charging network in Europe (Ecotricity, 2016). The price for a 30-minute rapid charge (43kw AC up to 50kw DC) is £6 providing up to 80% charge depending on battery capacity. This price increase needs to be considered when routing vehicles as it could have decisive effect on the outcome. In recent years the Electric Vehicle Routing problem and the Electric Vehicle Charging problem has attracted much attention from researchers, businesses and organisations. The number of papers as a result have increased exponentially.

There are a number of key factors that need to be addressed when addressing electric vehicles. The main factor that sets the electric vehicle apart from its conventional combustion counterpart is of course its electrical engine which is power by a set of batteries. The lithium-ion polymer batteries that are currently used to power the majority of electric vehicles are continuing being reengineered to provide a higher energy density in order to maximise the potential range of the vehicle. The Battery's efficiency can be become reduced over time known as degradation. Factors including temperature and over-charging have dramatic effect on a battery's degradation. Pischler and Riener (2015) studied historic electric vehicle data and were the first to use real world data. Their results show the large effect that temperature has on battery consumption. In cold instances around -5°C energy consumption was a factor of 2 greater than at 20°C. This temperature variable has not been included in any electric vehicle routing problems in current literature to the best of knowledge, but with such a large influence it proves to be of great importance. Charging times are also a topic of interest currently. Ramezani et al. (2011) design a simulation environment in which a set of charging schedules are developed, a multi-objective evolutionary optimisation algorithm.

S. Pelletier et al., (2014) provide a good review of current studies that use electric good vehicles for distribution. Bruglieri et al. (2015) develop a Matheuristic for the Electric VRP with time windows, here partial recharges are allowed. The Matheuristic develop combines Variable Neighbourhood Search with Branching the research outlines possible areas for development in this area. Sassi et al (2014) consider a new real-life heterogeneous electric vehicle routing problem with time dependant charging costs and a mixed fleet (HEVRP-TDMF). Customers here are served by a mixed fleet of Normal vehicles and Electric vehicles with varying battery capacities and operating costs. The objective is to minimise the number of employed vehicles and then minimise the total travel and charging costs. A mixed Integer programming Model was used to develop a charging routing heuristic and a local search heuristic based on the inject-eject routine with three different insertion strategies. While identifying the limited range of the vehicle they do not take into consideration the load of the vehicles and the added energy demand that will be generated due to the additional weight. Fiori et al. (2016) devise a power-based energy model for electric vehicles. The authors consider a model that computes the regenerative braking efficiency using instantaneous vehicle operation variables. The study found that driving in urban areas result in a much higher amount regenerative energy regenerated compared to high speed motorway driving. It was also found that the use of air conditioning and heating systems severely changes the EV efficiency and driving range. Felip et al (2014) were the first to bring real life constraints into the Erdogan and Miller-Hooks (2012) model, factors including partial recharges and cost due to battery amortization. The authors also incorporate various charger types available slow/medium/fast/ultra-fast with different associated costs per KWh consumed. The model combines constructive heuristic methods with local search, 2-opt, reinsertion and simulated annealing. The instances used are adapted from classical Soloman, Erdogan and Miller-Hooks (2012) and also the ones proposed in Schneider et al. (2014). Two dataset configurations are considered, a centrally located depot and a corner depot location configuration. Partial recharges increase the savings associated with the electric vehicle routing problem and on average increase with the size of the problem and help with feasibility of the problems. The authors found that more available technologies gave the vehicles more options when it came to options for the recharge. In order for electric vehicles to be viable for consumers a strong infrastructure needs to be in place. This infrastructure will have a number of available charging stations with a range of charger types. Planning of these electric infrastructures are becoming of increasing interest, making research of the Electric VRP more significant (He et al. 2013, Mak et al. 2013, Nie and Ghamami, 2013 and Wang and Lin, 2013). The future Infrastructure of new fuelling stations is an interesting development and manufacturers such as Nissan believe they will play a key part in general life. They believe that charged by renewable energy sources cars can be used to create store and distribute renewable energy. Through intelligent battery and drive technology moving towards a greener energy infrastructure could be possible. Using inductive wireless charging and autonomous vehicles, future vehicles could autonomously charge themselves in inductive charging spaces, and then re-park to let other vehicles charge in the same bay all at night. Come the morning houses and streets could draw energy direct from the vehicles powering your home as you start your day. Nissan call these smart streets, a street that's connected and integrated that can sync roads and grid. Recycled electric vehicle batteries can be converted into smart home energy storage systems so no clean energy goes to waste. With zero emission technology you can drive straight into work or office and your vehicle can then be charged or even power your office. Car parks could be replaced by green areas of grass and trees providing a kinder greener environment. Zero emission and autonomous vehicles can be the future. With these prospects it opens up exciting and new areas of research that will be key areas for development to ensure that these infrastructures are as efficient as possible.

2.3 Emissions

In the traditional VRP, the focus is concentrated on the economic impact of vehicle routes taken by an organizations fleet of vehicles. Sustainable logistics adds to this model and pose new models with varying applications. Green logistics involves measuring the environmental impacts formed from different routing strategies, reducing fuel/energy consumption and managing waste disposal (Sbihi and Eglese 2007). The topic was first discussed in literature in 1990 (Srivastava, 2007) with Palmer (2007) being the first to introduce environmental issues into the VRP, differing from previous work that estimated environmental savings based on distance or duration of journey time. Other issues were considered including road gradients, congestion and speeds generating an emissions matrix. These VRP variants are often known as *Green Vehicle Routing Problems (GVRP)* or the *Pollution Routing Problem (PRP).* The literature in this section will focus on the routing strategies and reducing fuel/energy consumption along with formulation. These GVRP variants have risen in literature in recent years although are vastly outnumbered by traditional VRP's. Via the online research library website Scopus green based VRP's account for less than 3% of the VRP's within research (that is available on scopus). However, given the latest concerns about environmental issues and increasing regulations, recently more VRP's are incorporating green aspects. Researchers are now looking at ways to improve the emissions crisis, efficiently managing vehicles will have a large part to play. Lin et al. (2014) provide a recent review on VRP's with environmental issues.

The GVRP was predominantly researched since 2006. Sbihi and Eglese (2007) presented some gaps in research of the GVRP by means of using Time-Dependant VRP approach for a minimizing emissions model. Limited scientific papers were produced on the green road freight industry previous to 2009; further work on emission based VRP's has been conducted by way of the Pollution Routing Problem (PRP). The PRP was introduced by Bektaş and Laporte (2011). The PRP seeks to optimize both the distance and speed with respect to time constraints. The problem is difficult to solve, and so heuristic and metaheuristic methods are often used to solve it. Demir et al. (2012) proposed an adaptive large neighbourhood search metaheuristic in a sequential method. Primarily the solution method is computed using a fixed speed after which a post optimisation occurs where variable speeds are allowed. Kramer et al. (2015) however show that this method can in some cases lead to lower quality solutions, the authors formulate a new hybrid iterated Local Search matheuristic approach to solving a problem with objectives to minimize operational and environmental costs while respecting capacity constraints and service time windows. This method outperforms previous methods from literature and is capable of high-quality solutions.

As air-pollution has become a larger, growing threat in recent years organizations such as governments and private companies have begun to become environmental conscious. The UK Government has decided that the environmental impact is to be a primary concern for current and future party leaders (www.gov.uk/government). Logistic activities such as transportation, product production and development and waste management can have a great impact on the environment requiring investigation into techniques and strategies to reduce this threat (see figure 1.1.1). Transportation, while being the most fundamental infrastructures for economic growth also provides a large proportion of pollutants (Salimifard et al., 2012). Transport schedulers should put emphasis on efficiently packing loads, avoiding empty runs, optimising vehicle routes, educating drivers with fuel efficient tips and employing technical solutions. Drivers have a massive influence on the emissions they create themselves. Using the telematics data acquired from a Logistics based company in the South East of England. It was observed that the difference in vehicle emissions between the best and worst drivers can be as much as 15% over a 250-mile trip. Within road haulage solutions such as fixed side walls and wheel wraps can be incorporated to improve aerodynamics leading to a reduction of 7-12% (Bode et al. 2011), for more information regarding aerodynamic trailer devices for drag reduction the reader is directed to Hakansson and Lenngren (2010) for further information and results about the benefits of drag reduction techniques. Low resistance rolling tires can be used to further reduce fuel consumption and can see benefits by as much as 6%. Researching into the relationship between environmental impact and transportation through route planning will be able to provide further understanding and practical suggestions to benefit the environment. Improving transportation efficiency at an operational level is the most straight forward action when researching green logistics. A decrease in fuel consumption can similarly provide a reduction in harmful polluting greenhouse gas emissions (ErdoÄŸan and Miller-Hooks, 2012; Xiao et al., 2012). The existing literature on VRP concerning fuel consumption seems limited in comparison to traditional VRP's. However, several papers do try and incorporate accurate fuel consumption models. These fuel consumption models use a combination of variables including load, speed, distance, gradient and vehicle characteristics. Speed and load can have a dramatic effect on a vehicle's emissions and are often the factors most associated with emissions. Figure 2.3.1 represents the resulting emissions from a variety of heavy-goods vehicles (HGV's), notice that the least emissions occur at different speeds for different vehicles which adds added complexity to models, that needs to be added to improve accuracy and real-life usability. In real life situations speed limits will need to be factored in and these could also have bearers on the route decisions.

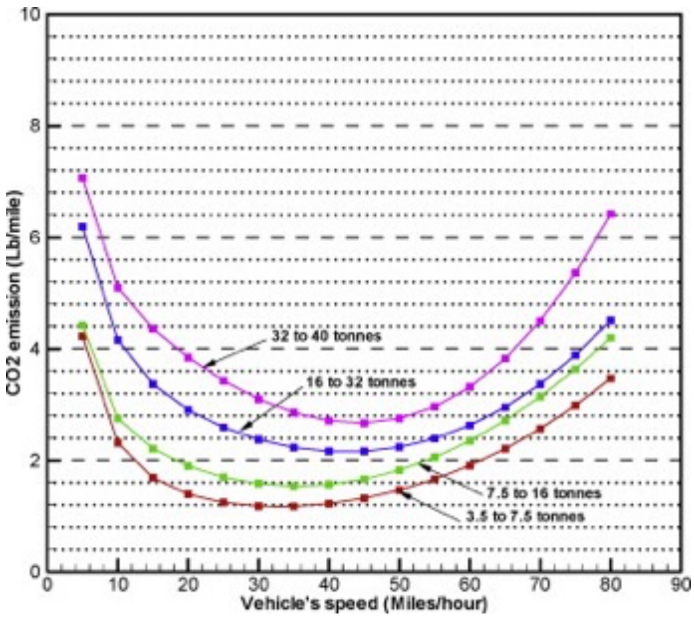


Figure 2.3.1 Relationships between CO2 emission rates and travel speeds of HGV's (Xiao and Konak 2015)

However, other factors including driving styles, road geometry and weather conditions also have an influence on fuel consumption. Xiao et al. (2012) provide a fuel consumption model that is popular among researchers. They proposed a Fuel Consumption Rate (FCR) which was incorporated into an extended CVRP model (FCVRP) with the aim of minimizing fuel consumption. Both the distance travelled, and the load are used as the factors which determine the fuel costs. FCR is taken as a load dependent function, where FCR is linearly associated with the vehicle's load. Papson et al. (2012) developed the transportation speed to fuel consumption model and applied it to Time Dependant VRP's. For more Fuel consumption model papers, the reader is directed to Fagerholt (1999), Apaydin and Gonullu (2008), Maraš (2008), Nanthavanij et al. (2008), Sambracos et al. (2004) and Tavares et al. (2008). Li (2012) propose a mathematical model to formulate a model to solve a VRPTW with the objective of minimising fuel consumption. Factors such as distance, speed and load are taken into account as well as wait time. The fact that a vehicle may consume fuel while stationary can occur for a number of reasons including heating/cooling the driver's cab. The method for measuring fuel consumption is similar to that of Suzuki (2011). Fuel consumed expressed as miles per gallon (MPG) along arc (i,j) can be expressed as:

$$MPG_{ij} = (\alpha_0 + \alpha_1 v_{ij})\gamma_{ij}\pi_{ij} \qquad (5)$$

Where v_{ij} is the average speed in arc (i,j), α_0 and α_1 are parameters to be estimated (≥0), γ_{ij} is the road gradient factor $\gamma_{ij} = 1$ is for flat terrain, (> 1 is for a negative gradient and < 1 is for a positive one). $\pi_{ij} > 0$ is the load factor parameter. This load parameter is expressed as a linear function: $mpg = \beta_0 + \beta_1 L$ where L is load, $\beta_0 \geq 0$ is the mpg of the vehicle when empty, $\beta_1 < 0$ is the coefficient measuring the loss of mpg caused by additional load. And so π_{ij} can be described as:

$$\pi_{ij} = \frac{\beta_0+\beta_1 \sum_{i\in Y_{ij}} d_i}{\beta_0+\beta_1\mu} \qquad (6)$$

d_i is the weight of the load to be delivered to customer i, $Y_{ij}$is the unvisited customer list when travelling on arc (i, j), μ is the average vehicle load. In order to calculate the fuel while remaining stationary (or wait time consumption if delivering goods with engine running) a parameter $\rho \geq 0$ is used to denote the average amount of fuel consumed per hour while the vehicle is stationary waiting at customer sites. Therefore, at customer i the fuel consumption during wait time w_i can be described as

$$WGPH_i = w_i\rho. \qquad (7)$$

Vehicle emissions are affected by many factors as have been described in this section of the literature review. Factors including load, speed and road geometry will be introduced into the platooning model in Chapter 3.0.

Fuel consumption is related to a number of factors, these can be broken down into core variables or resistances: rolling, grade and aerodynamic resistances. In order to reduce fuel consumption these resistances need to be reduced effectively reducing the required power of the engine to power the vehicle. Rolling resistance is related to the frictional losses as well as the mass of the vehicle, they can be reduced by incorporating factors mentioned previously including low resistance tyres. Low resistance tyres reduce the rolling resistance constant. Grade resistances are directly related to the weight of the vehicle as well as the angle of the incline or decline, and so can only be realistically reduced by reducing vehicle load or by routing along different terrain with fewer steep inclines. The final resistance that directly effects fuel consumption is the aerodynamic resistance. This value is determined by the drag coefficient of the vehicle as well as the velocity. This aerodynamic drag resistance can be reduced by tweaking the aerodynamic design of the vehicles thereby reducing the drag coefficient. Figure 2.3.2 below is created using real life data acquired from (Engineering Toolbox, 2016) and implementing the resistance equation that is formed in the next chapter where it will be explained in more detail. The figure represents the forces acting on a HGV travelling at various speeds on a constant gradient. It can be seen that the aerodynamic force does not become the more dominant force until speeds of 70km/h +. In chapter 3 a comprehensive fuel consumption experiment taking into account these resistive forces is conducted and the results reflect the data shown in Figure 2.3.2.

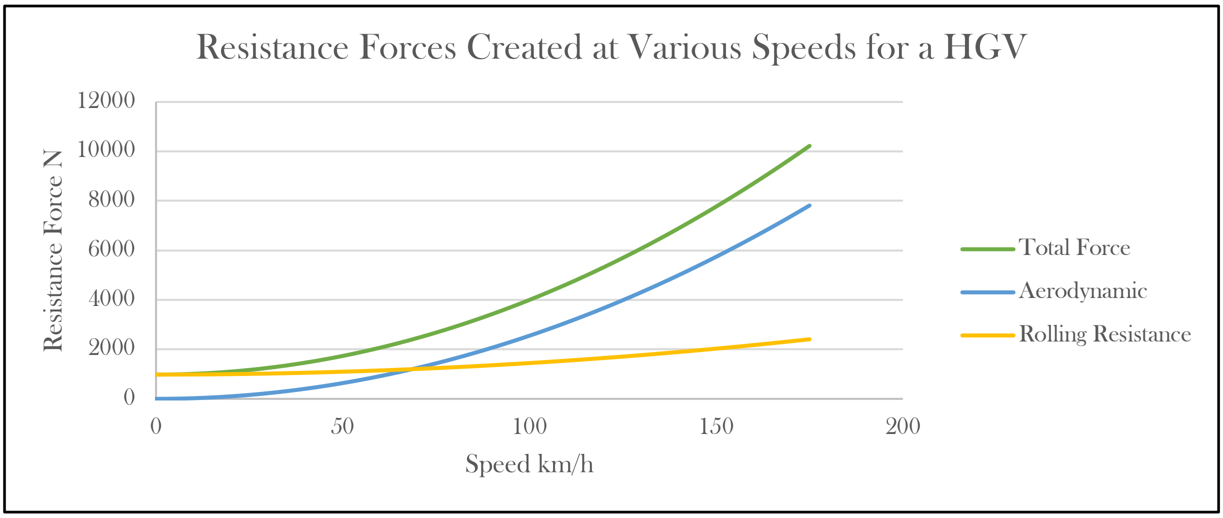


Figure 2.3.2 Total resistance forces created at various speeds on a constant gradient for a HGV

When investing in aerodynamic improvements assessments into what the vehicle will be used for and the general operating speeds can be highly influential upon the decision. This factor will need to be addressed in the proposed problems. It must be noted however, that the data represented in figure 2.3.2 is only applicable for HGV's, other forms of light goods vehicles (LGV's) will have significantly lower rolling resistances due to their reduced friction forces from a combination of less weight and less wheels as well as different frontal areas. Many LGV's have very poor frontal area designs, as such the aerodynamic force will be more prominent at lower speeds when compared to HGV's. Aerodynamic aids can be used to streamline the flow of air over a vehicles body, reducing fuel consumption significantly. Heavy duty truck improvements include systems such as shape changes and installations. These include: reducing the trailer gap by moving the fifth wheel and by using cab flairing's, trailer side skirts and undercarriage skirts, boat tail, integrated tractor roof fairings, aerodynamic mirrors, fuel tank flairings, aerodynamic bumpers, wheel flairings and hidden exhaust stacks (Green Transportation Logistics, 2015). Some studies in the UK conducted in 1999 found that trucks travelling at speeds 50mph and 56mph could see 9.3% and 6.7% fuel savings respectively (ETSU and MIRA 2001). While all these benefits require modifications on the vehicles, one technique doesn't, known as drafting/platooning it can be used to improve fuel consumption dramatically. In order to investigate the full benefits that platooning can bring into transport systems, an accurate and reliable way of measuring vehicle emissions is needed; these techniques can then be introduced into the platooning model to provide real tangible results.

2.4 Platooning

Drafting/Platooning provides aerodynamic benefits by reducing the drag of vehicles, this can be utilised within the logistics industry to significantly reduce emissions. A Platoon is described as a group of vehicles of minimum group size one. It has exactly one platoon leader and zero or more platoon followers. A platoon can perform different platoon operations (Maiti et al. 2017). Although a proper platoon consists of more than one vehicle. The platoon can be split into 4 properties:

- ID – The platoon ID identifies the platoon from other platoons allowing the user to easily differentiate, this includes the platoon size and the capacity of the platoon.
- Location – This refers to the platoons longitudinal and latitudinal coordinates within the system. The platoon has a definitive start and end point, although can create multiple platoons in a single route. This is a dynamic property.
- Gap – there must be a min-max allowance gap between the platoon of vehicles. This value depends upon the speed of the vehicles, the size and shape of the vehicles as well

as the technology on board. While this thesis will not delve into the factor it has been extensively investigated within literature (Swaroop and Hedrick, 1999)(Broggi et al. 2000)(Alam et al. 2010).

- Speed Limit – The speed limit of a platoon defines the amount of benefit gained and the quantity of fuel consumed. Below a certain speed the effect is nullified, increasing the speed excessively can also lead to potential traffic incidents.

Platooning is the term used to describe a series of HDV's or Trucks following one another along a stretch of road, an example can be seen in the figure below.

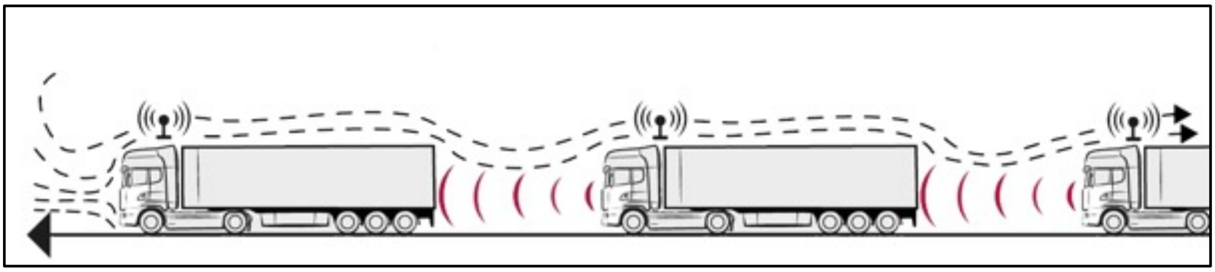


Figure 2.4.1 HDV's platooning close to one another reducing air drag for trailing vehicles, controlled via radar and wireless communication. Figure is adapted from Scania Newsroom (2016).

Figure 2.4.1 shows the vehicles using sensors to maintain a short gap between them in order to reduce fuel consumption. A radar allows vehicles to perceive their environment allowing them to accelerate and brake according to the vehicle/object in front of them. Vehicle to Vehicle communication allows the vehicles to better coordinate themselves for cooperative driving. As a vehicle's speed increases so does the drag force acting on it. At a speed of 60mph HDV engines use over 60% of available engine power to combat aerodynamic drag, and so by reducing this force it can have a dramatic effect on fuel consumption (Freight Best Practise, 2016), especially at higher speeds (Scania Newsroom 2016), this can be clearly seen in figure 2.3.2. A 25% overall drag saving would result in around a 15%-20% fuel saving depending on truck loading based on a flat road (Hammache, Michaelian and Browand, 2002)(Scania Newsroom, 2016). Fleet Management Systems (FMS) are commonly used among fleet operators. FMS enable the fleet operator to analyse and monitor many different conditions of each vehicle such as speed, position and fuel consumption. Knowing the speed and fuel consumption of a vehicle in operation can allow a decrease in fuel use a GPS systems that allow the FMS operator to improve driver performance; a key to reducing emissions. The position data provided using GPS tracking allows information to be used for Intelligent Transport Systems (ITS). Examples of ITS dedicated to advance research and improve the deployment of such systems include worldwide agencies include ERTICO in Europe, ITS America, ITS China, ITS Japan. Research for platooning as known today began in 1991, when technology was more viable for support such practise. PATH a Californian research program was one of the first to test platooning with two vehicles at highway speeds. (Chang et al. 1991). Most studies on fuel reductions in platooning have been on HDV's (Browand et al., 2004; Zhang and Ioannou, 2004; Alamet al., 2010; Tsugawa, 2013) where the potentials are greater due to the shape of the vehicle. A fuel experimental study with mixed cars and HDVs in platoons has been done in Davila (2013). All studies indicate a fuel saving for the follower vehicles from the air drag reduction and this is achievable through vehicle control. However, the controller also has an influence the fuel consumption. With controllers constantly adjusting the vehicles speed, there is a danger of increased consumption through constant acceleration/deceleration, this control is largely down to the topography of the land and the ability to plan for inclines etc. Platooning/Drafting is rarely mentioned within routing literature however can have a profound effect on fuel efficiency, increasing dramatically the closer you get to the lorry in front. In road tests researchers achieved almost a 20% improvement in fuel economy (Haab, 2007). While the safe recommended distance is 2 seconds driving at 60mph in the dry this equates to a 53.6m gap, however the effects of drafting are still noticed at distances surpassing 50+m the benefits are reduced. Further testing is needed at longer distances to monitor the effect. Driving within the safe recommended distance can cause accidents and isn't advised. However, one way in which it can be monitored and plausible is with the introduction of autonomous vehicles. Autonomous driving eliminates the reaction time meaning that vehicles could travel much closer together at higher speeds safely. It has been confirmed that testing would take place in the near future (Sky News, 2016). In terms of routing this means that vehicles may be preferred to travel together on the same road often not taking the shortest route as the benefit of fuel saving by drafting along the same road may outweigh the shortest route. This added factor can be included into routing models however the arcs within the model will not be able to be measured using Cartesian coordinate system to create the distances, rather a real network will need to be created that will allow vehicles to traverse along the same arcs. Alternative methods are discussed later within models created for this research. Autonomous vehicles will bring various changes to the current driving environment. The vehicles will be more connected providing a vast amount of real-time information improving efficiencies and safety and completely operated with on-board sensors (Talebpour and Mahmassani, 2016). In order for vehicles to have the largest drag reduction smaller gaps are favoured, however, with a reduction in driving distance separation increases traffic collision risks. Aggressive controllers are needed in order to avoid collisions, Alam et al. (2014) look in more depth about the collision avoidance for HGV's. Platooning has been researched in real life instances by a number of groups, although very few address a mixed fleet into the problem. SARTRE was the first project with mixed typed of vehicles in a platoon (Robinson et al., 2010). When introducing the concept of platooning into the VRP, certain challenges arise. The VRP by nature attempts to reach a set number of customers and return to its origin, and as such does not aim to traverse multiple vehicles along the same routes but rather disperse them amongst the network of arcs. The possibility of joint route planning for platooning has only been covered within the VRP lightly. Most research focuses on the formation of platoons and safety aspect involved within vehicle platooning Kavathekar and Chen (2011). Baskar et al . (2013) and Larson et al. (2013) are among the few papers that address methods for increasing vehicle platooning possibilities, and briefly acknowledge the difficulty in finding exact routing methods. Larsson et al. (2015) is as far as we are aware the only paper to formally define the platooning problem while attempting to maximise the amount of fuel saved by vehicles capable of platooning on a road network. The authors formally define the problem as follows, a vehicle routing problem concerned with minimising the fuel consumption by platooning trucks given a collection of starting points, destinations and deadlines. The paper targets the German Autobahn network in particular and is used to create the road network, same node starting is also considered. Three different heuristic methods are used including the Best-Pair heuristic, Hub heuristic and a Local Search based heuristic. Of the three heuristic methods used the local search was the best in the majority of the testing. Further investigation into other heuristic and metaheuristic methods could provide more insight into the speed and accuracy of such methods, providing advice on the benefits of such methods. The run times of such methods are not known as they were not provided. Platooning is a new area to be considered in VRP, the implementation can be very beneficial when aiming to reducing emissions and is also applicable to real world road networks.

2.5 Literature Review Summary

The literature discussed within this chapter has identified possible ways in which the VRP variants can be considered to be Green. We hope that within the subject area of the VRP researchers will include more information regarding the emissions created when routing a set of vehicles and ways in which their chosen method has reduced them. Within this Thesis we have chosen to use a combination of the variants discussed to provide a comprehensive model that allows us to reduce emissions while remaining applicable to real-life instances. Electric vehicles are becoming increasingly mainstream, with the advancement in technology batteries are becoming more efficient and they can now be used in a large number of applications within routing problems. Electric vehicles provide a reliable autonomous vehicle which opens up a range of possibilities including driverless deliveries and platooning. Platooning is a new concept where the literature is mainly concentrated on functionality of the software the vehicles employ in order to maintain safe close distances. While a few studies have investigated platooning on road networks, to the best of our knowledge a platooning model has yet to be applied to a VRP investigating the optimum point at which vehicles should start and end their platoon.

Chapter 3

Basic Platooning

This chapter introduces the real-life benefits of Platooning along with theory of the process. Following the introduction and theory this section then looks at modelling the problem. In this Chapter the problem is split into 2 phases, the initial phase is based much around a CVRP whereby heuristic and metaheuristic methods are applied to improve the vehicle solution before the second phase introducing a Basic Platooning model; following on from the metaheuristic methods the CO_2 is calculated for the current model. This CO_2 calculation is used for the future objective functions as the distances may increase due to platooning. The Basic Platooning method used here maintains current customer locations, i.e the split point is fixed at a customer location only.

3.1 Introduction

Platooning is a new technique that is being introduced in the heavy goods industry. Similar to drafting in sports such as cycling and motor racing, the aim of platooning is to reduce the drag resistance of a vehicle by following another vehicle in tandem, together these vehicles form a platoon. Platooning can be further extended, and multiple vehicles can be included in the platoon each receiving drag reduction benefits. Aerodynamics play a critical role in the efficiency of vehicles; an effective design allows the vehicle's body to move easier through the air. As the vehicles speed increases so does the opposing force of drag proportionally. Therefore, at greater speeds drafting/ platooning becomes more effective. When a heavy goods vehicle is driving at motorway speeds it is offsetting a huge volume of air. Figure 3.1 shows this air displacement in action. The blue zones show low-pressure areas, the red zones show the high-pressure zones.

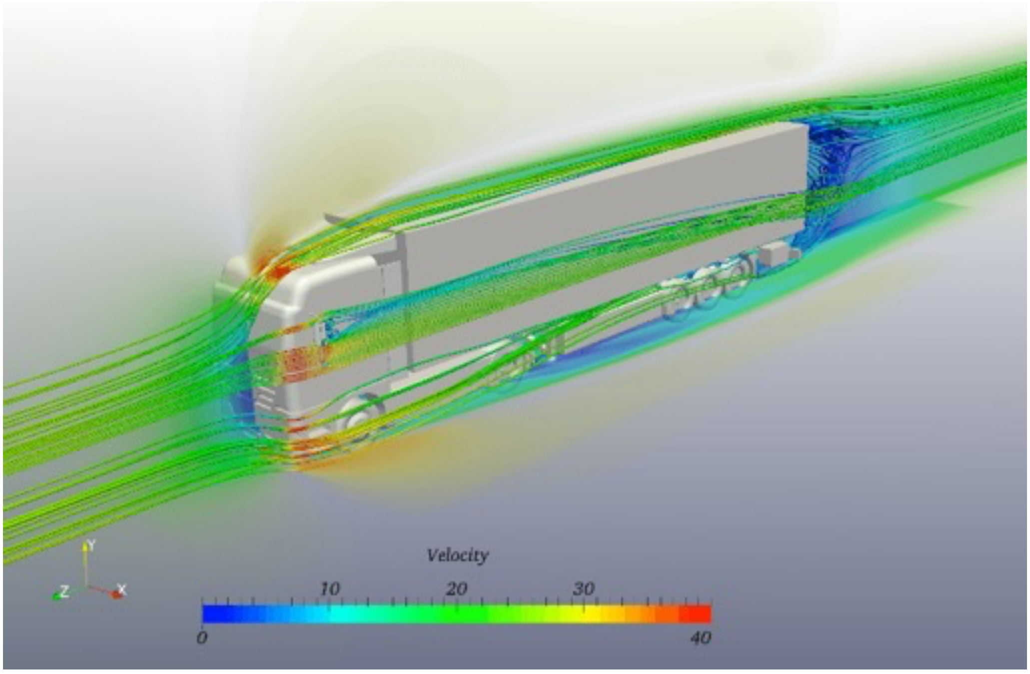


Figure 3.1.1 CFD simulation of a HGV and trailer travelling at 28m/s

The air hitting the front of the HGV is travelling at 28m/s when it hits the front of the vehicle, most of the air is then forced around the extremities of the cab, down the sides of the trailer and the around the rear of the trailer. The low-pressure zone is greatest at the rear of the trailer, at this point the air velocity is less than 10m/s creating a void where the air can actually create a vortex effect (vehicle wake) pulling the trailer backwards. For more information regarding vehicle wakes and its effects the reader is directed to Carpentieri, Kumar and Robins (2012). It is within this wake/area of low-pressure that a trailing vehicle can gain aerodynamic benefits and effectively reduce the drag force. Platooning not only benefits the trailing vehicles however. The lead vehicle also gains an aerodynamic benefit, as the vehicles wake is reduced as the area of low pressure is partially filled by the trailing cab. The distance of which the trailing vehicle is following is very important, too far away the drag benefits are reduced, too close and becomes dangerous due to driver reaction times and braking distances. The required technology has only recently been achieved that allows vehicles to follow each other safely at very close distances. A series of electronic monitoring devices as well as radar are used to generate semi/fully autonomous vehicles capable of platooning effectively. With the transport industry trying to identify new ways to save money, aerodynamics is a top concern. Reducing the drag force can lead to increased efficiencies and therefore reduced costs and emissions. Platooning can reduce CO2 emissions by up to 16% for trailing vehicles and as much as 8% for lead vehicles (ITS4CV study, Ertico). Secondary real-life benefits include delivering goods faster, extending the driving range and reducing traffic jams. Autonomous driving also allows the operators to safely carry out other tasks such as administrative work or taking phone calls. This chapter looks at the current literature around this driving technique as well as identifying its real-world benefits. A model is generated with concepts of how it can be introduced to the VRP and other transport systems.

3.2 Theory and Real-Life applications

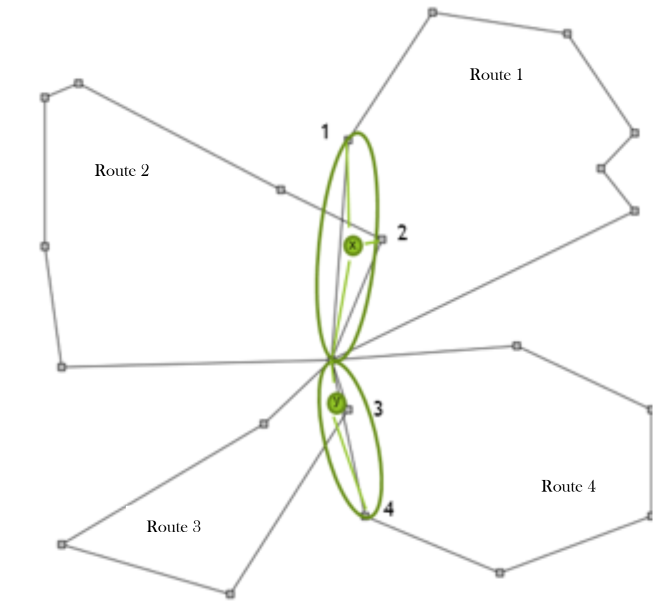
A main factor to consider when trying to reduce the fuel consumption of a vehicle is its aerodynamic drag properties. As can be seen in figure 2.3.2. In order to reduce this value, the drag coefficient of the vehicle must be reduced, one effective way is by reducing the frontal area of a vehicle. When one or more vehicles follows another in close proximity (often referred to as drafting) the trailing vehicles can effectively reduce their frontal area due to the vehicle in front punching a hole through the air. This technique is common in motorsport and cycling whereby vehicles/competitors can gain speed over their opponents. The term platooning is used when referring to vehicles actively drafting each other on the road. Platooning of vehicles is largely affected by the speed and the distance between the vehicles that are drafting.

In order for vehicle platooning to be most effective the distance between the lead and trailing vehicle needs to be very close. The optimum gap between the vehicles in the platoon cannot be met safely when driving on normal conventional public roads with human drivers in full control due to reaction times and human error. Although, with recent technological advances in driverless technologies, electronic systems providing accurate and safe control over platooning vehicles allow close driving distances to be achieved, opening a new door in transport logistics. The lead truck will be under full human control all of the time, drivers of the trailing vehicles can then switch their vehicle into platoon mode which allows the on-board systems to monitor and control the distance between lead and trail vehicles continuously. These systems will take full control of the vehicle, removing human reaction time error meaning the vehicles will have the ability to simultaneously brake and accelerate, effectively connecting the vehicles into a platoon. Many logistic companies try to maximise their vehicle packing loads in order to make their vehicle as efficient as possible however often they cannot get the required delivery into 1 vehicle and so others are required. Other circumstances where multiple vehicles are involved can be when the customers are fixed otherwise known as a fixed route planning. Real life routes often involve vehicles following the same routes for the majority of their trip, send multiple vehicles to the same locations/ customers. This is the case within the South East of England whereby transport companies will use the main motorways such as the A2 and the M20 for the majority of their routes.

Vehicle Platooning is becoming a hot topic in the road freight industry, it compromises of several vehicles equipped with state-of-the-art driving support systems closely following one another. These form the platoon of vehicles, driven by smart technologies communicating between them. The primary benefit from platooning includes a reduction of fuel usage and therefore CO2 emissions, other benefits include the ability to perform alternate tasks (such as rest breaks) while driving in the platoon, although this is largely down to the autonomous vehicle functionality and a reduction of congestion. Fuel cost is the primary concern for transportation companies, and fuel equates for a third of the total operational costs of an HDV (Schittler, 2003). The European white paper (2011) has also produced targets of reducing carbon emissions by

60% by 2050, such a task can only be achieved by a multifaceted approach. By driving in a platoon formation, vehicles can reduce fuel consumption by as much as 20% (Robinson et al., 2010). These benefits depend on the speed of the vehicles and the distance between them. For the following instances, we assume that the vehicles all have a fixed speed, this fixed speed equates to a fuel reduction of 20% for the tow vehicle and 5% for the lead vehicle (Tsugawa et al. 2000). The lead vehicle is the vehicle which leads the platoon, this vehicle will receive the least benefit from platooning. The aerodynamic benefit for the lead vehicle is seen due to the reduction of turbulent air created from the rear of the trailer from the close trailing vehicles. The aerodynamic benefit for the tow vehicle is seen from a reduction in frontal drag area from following the lead vehicle closely. As mentioned previously speed has a large effect on the aerodynamic benefit excessive traffic can greatly reduce platooning benefits, since low-speed platooning would provide almost no reduction in aerodynamic drag. Since vehicles will likely not be platooning through large urban areas, we assume throughout that the time required to travel a road is fixed independent of time.

To allow the reader a more in depth understanding we will introduce a few examples to help demonstrate the basics of platooning. The first is using the Christofides 21 dataset, the second uses real-life road topography to highlight the benefits in real world instances. The first example we utilise our basic model, Steps 1-4 of the Platooning Algorithm found in Figure 3.3.1. The Platooning algorithm applied in step 4 acts as a post optimiser and is implemented after a good solution to the VRP has been found. This allows the comparison between a good VRP solution and the platooning solution in terms of distance and also emissions. For the following examples in this chapter platoon fuel savings of 6 % and 21% have been used and taken from the literature, these represent the fuel savings for the lead and tow vehicles, respectively. These values used for the platoon fuel saving can be found within the literature review in Chapter 2 section 4. Although the values do vary according to a variety of factors (e.g speed) for this example they will remain



Old Route	Gallons of Fuel	New Route	Gallons of Fuel
0-1	1.193	0-x-1	1.135
0-2	0.664	0-x-2	0.644
0-3	0.272	0-y-3	0.245
0-4	0.960	0-y-4	0.943

Figure 3.2.1 Christofides 21 dataset after performing the Platooning post optimiser. Benefits shown in table.

fixed, other factors are investigated in Chapter 4 where advanced platooning methods are modelled. Figure 3.2.1 shows how to merge 4 vehicles from 4 routes in 2 separate platoons. Starting with the optimal result in terms of distance for the dataset. 2 pairs of routes are chosen, in this example the chosen pairings are routes 1 and 2, routes 3 and 4. These were chosen based on their proximity to one another. In this insatnce the splitting point x was generated at a random point within the boundaires of a triangle formulated by the depot, route 1 customer 1 and route 2 customer 2 (please see Figure 3.2.1). The green lines demonstrate the new routes the vehicles travel. In this insatnce the total solution distance was increased by 0.99%, however the overall CO_2 was reduced by 3.95%. This large saving is a result of creating just two platoons. With the creation of more this could be further improved. We can now break this down further and inspect each of the processes and stages. In this instance the point at which the platoon separates are in this case taken to be the midpoint between the depot and the midpoint between the two first customers. This point at which they separate can have a large factor on the fuel savings, therefore optimising this point is essential. Further information regarding how this can affect the results is explored in Chapter 4. From this basic example a large reduction in CO_2 produced was seen, however, the benefits may vary according to problem type and customer location. The layout and dispersion of customers will have an effect on platooning's usefulness. Further investigation into the Platoon routing problem is needed in order to determine its effectiveness on various problem types and real road networks. By considering only the first arcs of each of the routes a triangle of possible platooning scenarios is created. Customers A and B are the first customers for 2 respective vehicles.

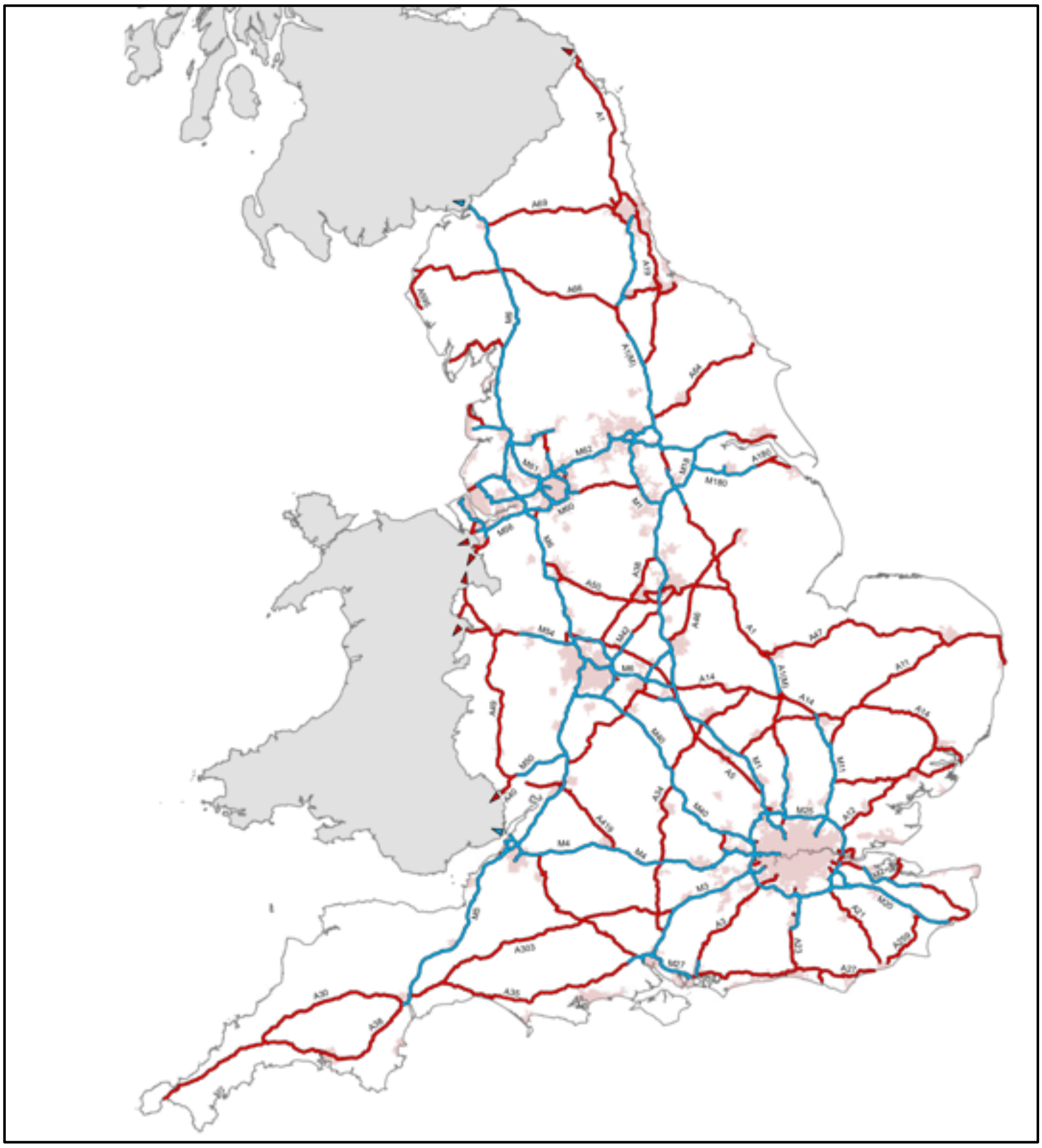


Figure 3.2.2 UK Road Network - Major A roads and Motorways

Within the UK road network 66% of traffic is traversed using motorways and major A roads (Road Use statistics, 2018 Gov.uk). These major roads are ideally suited to platooning, 2 or more

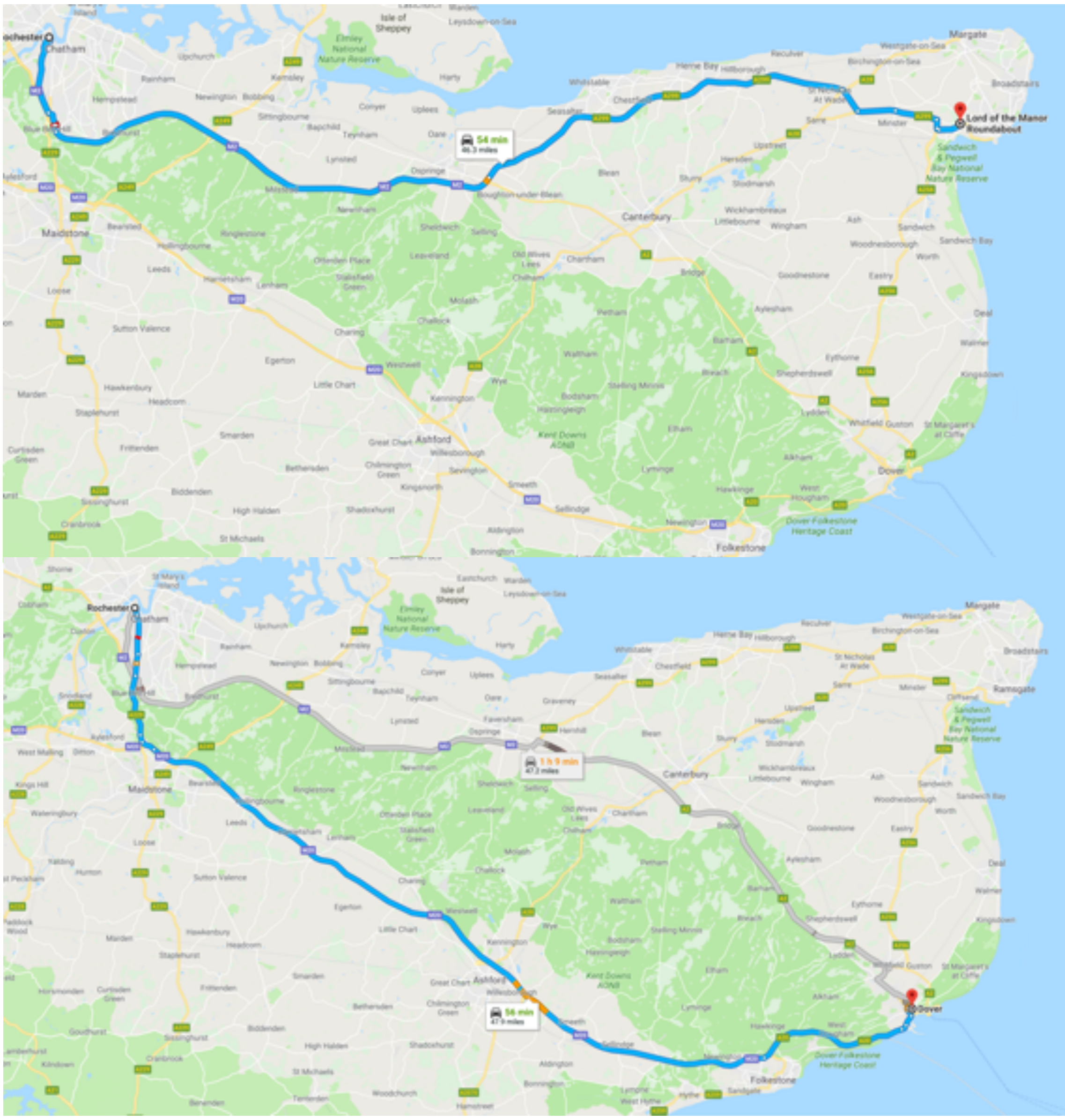


Figure 3.2.3 Two routes across the South East

lanes allow other vehicles to pass the platoons safely and allow the platoons to operate more efficiently as the larger roads allow drivers to see further ahead, allowing smoother braking and accelerating. For this real-life example we will highlight the southeast.

We consider 2 potential routes with Rochester being the depot and 2 customers for 2 vehicles one in Dover the other in Ramsgate. From figure 3.2.3 we can see both routes, with the fastest route calculated by Google Maps shown. In order to calculate the CO_2 production from the fuel consumption data taken from the US energy administration (2016) has been used, it can be assumed that 10.172kg of CO_2 is produced per Gallon of Diesel burned. In this particular example to make things simplified we have assumed that the vehicles all have a fuel consumption of 10mpg. Route 1 traverses from Rochester to Ramsgate, the route consists of 2 main roads the M2 and the A299 with a total distance of 46.3 miles and producing 47.09kg of CO_2 based on Route 2 traverses from Rochester to Dover, Google maps provides two potential routes when

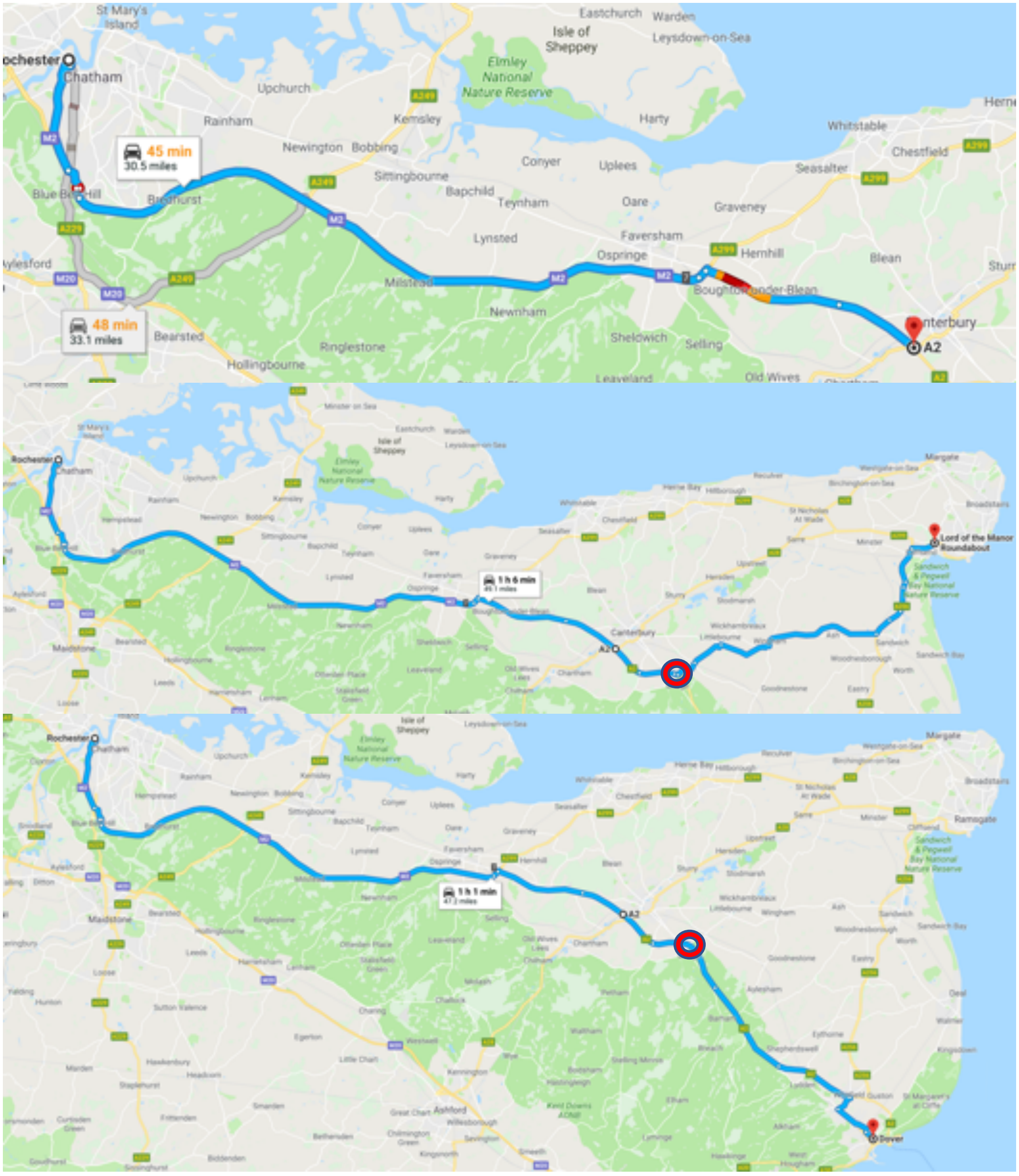


Figure 3.2.4 Two real-life routes with platooning.

travelling to/from these locations. In this particular example the travel times are skewed by traffic around the junction before Canterbury the M2/A2 interchange. The route chosen was calculated as the quickest, with a total distance of 47.9 miles and producing 48.71kg of CO_2. Figure 3.2.4 shows a common route and a potential platooning option down the M2 and beginning of the A2 between Rochester and a junction after Canterbury highlighted by the red circle, the platooning route is 30.5 miles in length. The vehicles would then split at the junction circled in red and continue along their separate roads, the A2 and a smaller B-road towards Dover and Ramsgate respectively. Assuming a 10% average saving from the 2 vehicles in tandem with an average consumption of 10mpg under normal conditions, route 1 from Rochester to Ramsgate now has a total distance of 49.1 miles with a production of 47.34kg of CO_2, route 2 from Rochester to Dover now has a total distance of 47.2 miles with a production of 45.41kg of CO_2. The combined overall length of the routes is increased by 2.2% to 96.3 miles however the CO_2 production has reduced by 3.05kg, resulting in a saving of 3.2%. This simple yet insightful example of platooning proves its potential when applied to the vehicle routing. Within larger transport systems the prospective benefits are even greater. Following on from these examples we will now investigate the problem further, modelling the problem and providing results as well as future directions for platooning. The following sections are divided into a 2-phase model. The initial phase is based around a core CVRP model this is expanded with the inclusion of emissions calculations as well as heuristic and metaheuristic techniques. Following this the second phase is introduced where the main platooning algorithm is applied.

3.3 Methodology

Our basic **Platooning Algorithm** used within this thesis can be seen in figure 3.3.1 and can be split into the following steps:

- Step 1 – produce initial solution using the Clarke and Wright Savings algorithm. See section 3.4.1
- Step 2 – Introduce the Variable Neighbourhood Search
- Step 3 – Emissions Calculation and Optimisation
- Step 4 - Platooning – formation of splitting points for joint routes

Figure 3.3.1 Basic Platooning Algorithm Steps

Steps 1-3 of our platooning model create good solutions whereby Step 4 and 5 employs the main and extended platooning algorithm. The models used within this chapter are based around a core CVRP model, further constraints and variables are then added to adapt the model to suit certain factors in later chapters. Different objective functions can also be chosen to optimise distinctive aspects. The core model that was created to be used within this project is used throughout the following variants and adapted to fit their required aims and meet their constraints.

3.4 Explanation of main Platooning steps

This section goes into depth about the algorithms that were modelled and tested within the Platooning Algorithm found in Fig 3.3.1. The majority of the examples shown to demonstrate the techniques used were tested using a small instance namely the Christofides 21 instance (1979), this was chosen as we can achieve a very good solution in a very reasonable amount of time allowing multiple runs to be carried out in quick succession. This section also identifies the effectiveness of classical heuristic methods, notably the savings method and the sweep algorithm. Using techniques taken from our Literature review in Chapter 2 initial routes are created using several algorithms including the Sweep and the Clarke and wright Savings. Slight modifications are introduced to further improve the initial results such as capacity limiting and altering the starting point of the sweep algorithm. Classical heuristics were mostly developed between 1960 and 1990 with metaheuristic methods following (Laporte et al. 1999). These classical methods perform a search of solution space and generally produce modest quality solutions in good computational time. They are able to be modified and adapted to account for a diverse set of constraints, and as such they are still used today in a wide range of commercial program solvers. The following section (Step 2) introduces several local search techniques and then applies the VNS method in order to improve the solution further. The tests are carried out on well-known instances from Christofides et al. (1979) and Golden et al. (1998), Table 3.3.1 provides the instances chosen in this research and the best available solutions known. The results and code were implemented using C++ in MacOS with the following specs: Processor - 4 GHz Intel Core i7, Memory - 16 GB 1867 MHz DDR3, MacOS Sierra. Once a good quality solution has been found the emissions are calculated in Step 3. This provides the user a base level on which to improve upon. Here load factors are introduced, and we perform analysis on the impact load can have on certain routes. Step 4 is when we employ our platooning algorithm. Here vehicles are paired together when leaving the depot and a splitting point is chosen for the vehicles to split the platoon. At this point the vehicles then continue along their respective routes visiting customers. Our basic platoon model is tested on the current solution obtained from Steps 1-3 and the emissions of the new platoon route are calculated.

Table 3.4-1 Best known results of the Chrsitofides et al. (1979) and Golden et al. (1998) instances (continued on the next page)

Instance	Name	Customer Size	Capacity	Max Route Length	Delivery Time	Best Known Solution	Published Results
Christofides, Mingozzi and Toth	1_50	50	160	∞	0	524.61	Rochat, Y., Tailard, E. (1995)
	2_75	75	140	∞	0	835.26	Rochat, Y., Tailard, E. (1995)
	3_100	100	200	∞	0	826.14	Rochat, Y., Tailard, E. (1995)
	4_150	150	200	∞	0	1028.42	Rochat, Y., Tailard, E. (1995)
	5_199	199	200	∞	0	1291.29	Mester, D., Braysy, O. (2007)
	6_50	50	160	200	10	555.43	Rochat, Y., Tailard, E. (1995)
	7_75	75	140	160	10	909.68	Rochat, Y., Tailard, E. (1995)
	8_100	100	200	230	10	865.94	Rochat, Y., Tailard, E. (1995)
	9_150	150	200	200	10	1162.55	Rochat, Y., Tailard, E. (1995)
	10_199	199	200	200	10	1395.85	Rochat, Y., Tailard, E. (1995)

Golden et al.	1_240	240	550	650	10	5623.47	Groer, C. (2008)
	2_320	320	700	900	10	8431.66	Nagata, Y., Braysy, O. (2009)
	3_400	400	900	1200	10	11036.23	Nagata, Y., Braysy, O. (2009)
	4_480	480	1000	1600	10	13592.88	Nagata, Y., Braysy, O. (2009)
	5_200	200	900	1800	10	6460.98	Nagata, Y., Braysy, O. (2009)
	6_280	280	900	1500	10	8412.88	Nagata, Y., Braysy, O. (2009)
	7_360	360	900	1300	10	10195.56	Nagata, Y., Braysy, O. (2009)
	8_440	440	900	1200	10	11663.55	Groer, C. (2008)

3.4.1 Initial Solution Method Step 1

The first step required is to build initial solutions. We compare two classical heuristic methods while including some modifications; analysing how they react to these modifications and how to further improve upon the initial solutions generated. We look at how these initial solutions are generated and how they are affected with different instances with different characteristics. To begin with a set of initial solutions is created using two heuristic methods. The first is the Clarke and Wright method (1964). In 1964 the Clarke and Wright algorithm was created as a solution to the VRP, the method is based on a savings concept. The savings algorithm does not provide a certain optimal solution however it does produce a relatively good solution. The basic concept expresses the cost savings obtained by combining two routes together and merging them into one route. i.e. initially customers are all visited individually. As transportation costs are given (route length) the savings result from combining two routes together can be calculated. The best routes are then chosen to be combined resulting in the best savings. Two methods can be used when merging these routes. The first is the sequential savings algorithm, this method works sequentially down the list of savings from best to worst merging routes till a constraint such as the max capacity is met. The routes are then merged, and the next route is calculated. The second version is the parallel savings algorithm here more than one route may be built at any time. In the general circumstances the parallel savings algorithm will produce better results however, dependant on the way the algorithm is implemented the parallel algorithm may be more computationally more expensive (Lysgaard, 1997).

The second way initial solutions are generated is the sweep method. The sweep algorithm is a method used for clustering customers into groups so that customers in the same group are geographically close together and can be served by the same vehicle. The depot is located first and set as the origin; the customers are then converted into polar coordinates with respect to the depot. The sweep then starts by visiting the customer with the lowest/or highest (depending on clockwise or anticlockwise sweep) angle and then increases/decreases the angle assigning each customer it approaches. The sweep is stopped when adding a new customer would violate the maximum vehicle capacity or maximum tour length.

The Christofides et al. (1979) instances are based around a cluster formation while the Golden et al. (1998) instances are radial around the depot. The effect this has on the solution quality of the proposed algorithms is clear within the results and should be considered in further research.

As mentioned before two well-known classical heuristic solution methods have been used, including a constructive method and a 2-phase algorithm. These solution methods were used to create an initial solution in an efficient time, the initial solutions are then incrementally improved by neighbourhood exchanges known as improvement procedures. The initial solution methods chosen include the Sweep algorithm proposed by Gillet and Miller (1974), (anticlockwise and clockwise) and a sequential Clarke and Wright Savings algorithm (1964).

The Clarke and Wright Savings algorithm (1964) is a widely known heuristic method for the VRP. It can be applied in both a parallel and a sequential technique. The algorithm that was chosen in this instance is the sequential technique and it can be found in Appendix 1.

The Sweep algorithm is used to form feasible customers initially formed by rotating a ray centred at the depot. A vehicle route is then obtained for each cluster by solving a TSP. The algorithm is as follows:

Assume each vertex i is represented by its polar coordinates (θ_i, ρ_i) where θ_i is its respective angle and ρ_i it the ray length. Assign a value of $\theta_i^* = 0$ to an initial arbitrary vertex i^* and compute the remaining angles of the other vertices in either a clockwise or anti-clockwise fashion. Rank these vertices in increasing order of their θ_i.

1. Choose a vehicle k.
2. Starting from two available vertices with the smallest angle between them and the depot, assign vertices to the vehicle k, providing the capacity and route length are not violated. If unrouted vertices still remain go back to Step 1.

Further from the basic Sweep algorithm we apply a modification, whereby all customers are considered as starting points with both clockwise and anticlockwise ordering considered. The modified sweep algorithm is applied as follows, steps 1-7 are considered to be the traditional method with steps 8 onwards being the improvement.

1. A radial line with a starting point at the depot starts from 0° in polar coordinates and sweeps through customer nodes surrounding the depot in a clockwise or anti-clockwise direction.

2. When the line reaches the first customer the customer is saved within a list.

3. The line is then swept again till it reaches another customer where it is then added to the list, this continues until all the customers have been saved in the list.

4. Using this list, the first customer is considered and the demand is checked to see if it violates the capacity constraint of the vehicle, if fit, it is assigned to route 1.

5. The second customer in the list is then considered; the total demand of customer 1 and 2 is considered and the capacity constraint applied and if acceptable customer 2 is assigned to route 1.

6. The assigning continues until the assignment of a customer violates the capacity constraint, at this point the current route is terminated by returning to the depot and a new route is created for the violating customer.

7. The method then continues until all customers within the list are assigned to a route.

8. The total route length is calculated and the route configuration is saved as the current best.

9. The list used in step 2 is then re arranged by moving the first member/customer to the end of the list.

10. The steps 3-7 are then repeated, if the new solution is better than the current best the route configuration is updated and saved as the current best.

11. The shuffling of the list continues until all customers have been considered as starting points.

This proposed method is similar to that of Wassan et al. (2008) except all customers are included in the initial sweep procedure. The authors' method excluded a set number of customers close to the depot from the initial sweep algorithm in order to reduce route rigidity (the exact number of customers excluded was decided after test results), our proposed modified sweep algorithm is also subjected to similar change in route rigidity; specifically in the capacity constraint for a similar required effect. The capacity constraint allowed in each vehicle in the initial modified sweep algorithm is reduced by 1% in each initial solution. By doing this, it removes some rigidity within the routes allowing flexibility to the improvement phase of the algorithm, whereby customers are inserted into a route where best fit. Once a solution has been produced the capacity is further reduced and the program is run again. For each run once the initial solution was found using the modified sweep algorithm stated above the improvement phase followed. New runs were created until the capacity was reduced to its maximum setting.

Route 1: 0-1-4-3-6-0

Route 2: 0-2-5-0

Figure 3.4.1 An example of a set of routes denoting which customer they are visiting

Figure 3.4.1 is an example of how these routes are constructed, the 0 position denotes the depot (each route starts and finishes at the depot), with each subsequent number representing the customer number which is predefined within the dataset. In this example when the sweep algorithm was attempting to visit another customer after customer 6 in route 1 the capacity constraint was violated and so the routes closes, and the vehicle is returned to depot. A new route is then created (route 2) by resuming where the previous sweep ended and then visits customer

2. Once all the customers have been included in a cluster the algorithm stops. On certain occasions such as a heterogeneous fleet multiple sweeps may need to be used for different vehicles.

Figure 3.4.2 shows the initial sweep result. The starting point is marked with a red circle, as this is the anticlockwise sweep method the next point visited is circled in green. This method creates good open routes however when a fixed starting position is used sometimes routes may be created with bad tightness, i.e some routes may have a low demand/capacity.

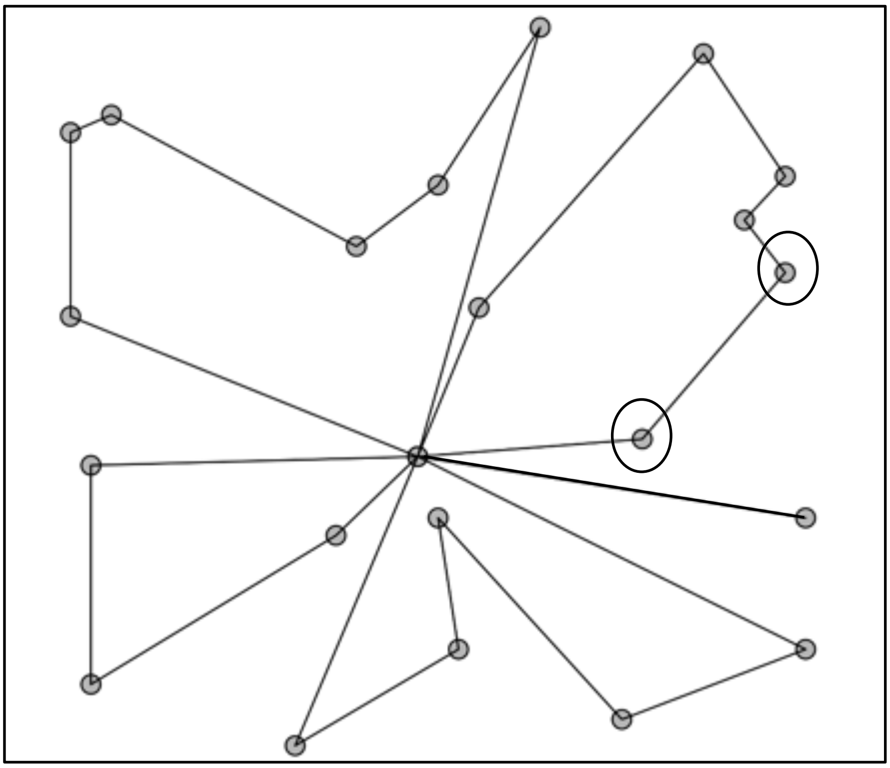


Figure 3.4.2 Initial Anti-Clockwise Sweep Result on Christofides 21 dataset.

Tightness is defined as the capacity of load in the vehicles divided by the total capacity of vehicle. The route highlighted in green shows that if a poor starting position is chosen that single routes may be generated causing an extra trip, that could be avoided if routes were better optimised. The standard sweep method for the VRP has produced a VRP solution, however to further improve this sweep method we can modify this heuristic by varying its starting point. The sweep method is implemented again by altering the list of customer's angles. The original angle lists are sorted either ascending or descending depending on whether clockwise sweep or anticlockwise sweep is chosen. The original sweep method creates routes using the first customer within the list and then continues onto the second etc. By shuffling the top member of the angles list to the bottom, a new starting point for the sweep algorithm is created. Tables 3.4-2a and b demonstrate an example of what these lists look like during the order change with them showing the order of customers before and after the change respectively. The sweep algorithm always begins with the first customer in the list, and so each New Angle List generated provides a new starting point.

Table 3.4-2a and 3.4-2b. Changing start position of the sweep algorithm to find best initial solution

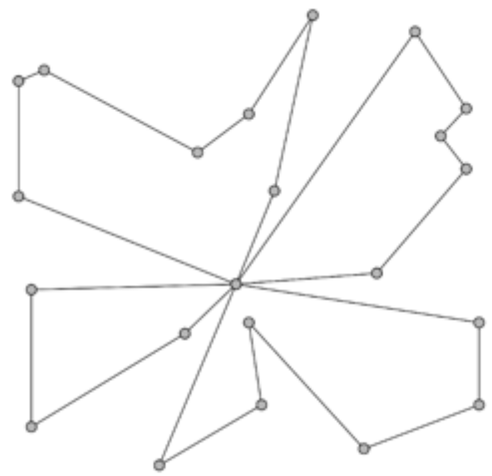
Table 3.4a

Original Angle List	
Customer Number	**Sweep Angle °**
1	2
2	15
. .	. .
.	.
10	320

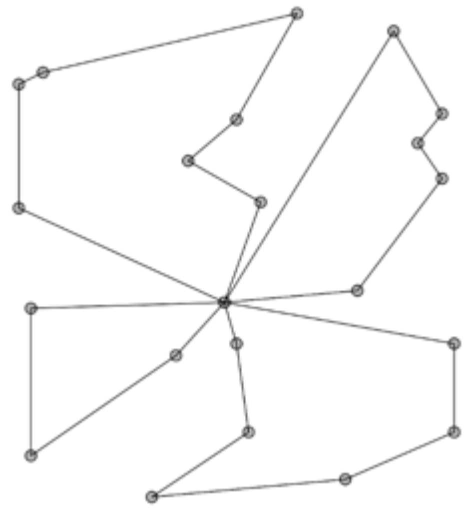
Table 3.4b

New Updated Angle List	
Customer Number	**Sweep Angle °**
2	15
3 . .	45 . .
10	320
1	2

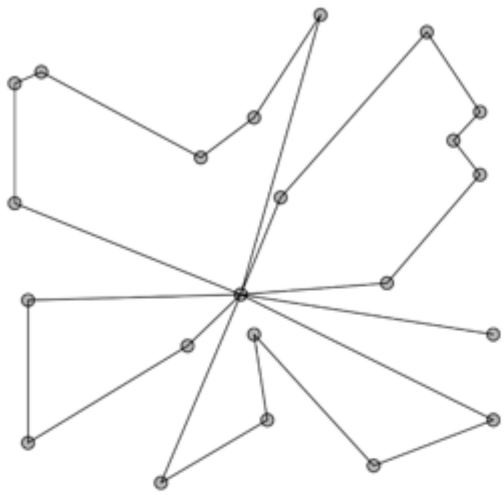
After each new sweep is implemented an Intra-Route Improvement heuristic is implemented before the solution values are generated. The Intra-route improvement heuristic used is the Or-opt (Or ,1976) it works on a single route looking at all customers within that one route. The one used on these initial sweep solutions moves only a single customer. It works first by identifying the first route size n and looks at the first visited customer $i = 1$ as a candidate to be inserted. i is then switched with customer in position j, where $j = i + 1$, j is then increased by 1 while $j < n - 1$, this avoids using the depot as a potential candidate for the intra-route. If a better solution is found this is saved as the new best solution. Using this new best solution, the next iteration begins starting with customer $i + 1$ as the customer to be inserted. Once all customers in the route have been inserted the best overall solution is saved and updates the current solution, the heuristic moves onto the next route. The diagrams in figure 3.4.3 shows the benefits of the Intra-route heuristic saving on average 11.6%.



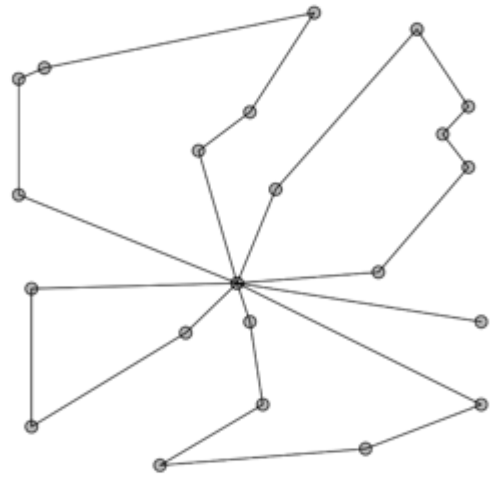
Clockwise Sweep Solution using the best starting position with no Intra-Route. Solution = 454.2 Number of Routes 4



Clockwise Sweep Solution using the best starting position with Intra-Route. Solution = 400.4 Number of Routes 4



Anticlockwise Sweep Solution using the best starting position with no Intra-Route. Solution = 488.64 Number of Routes 5



Anticlockwise Sweep Solution using the best starting position with Intra-Route. Solution = 432.62 Number of Routes 5

Figure 3.4.3 The effects of the Intra-Route Heuristic on the Christofides 21 dataset after initial sweep solutions.

Tables 3.4-3, 3.4-4 and 3.4-5 display the results from the initial solutions using the chosen classical heuristic methods.

Table 3.4-3 Initial solutions generated using the Sweep algorithm in an anticlockwise procedure.

Name	Customer Size	Capacity	Max Route Length	BKS	Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	668.826	5%	0.0014
2_75	75	140	∞	835.26	969.678	16%	0.0029
3_100	100	200	∞	826.14	959.235	19%	0.0051
4_150	150	200	∞	1028.42	1232.71	28%	0.0111
5_199	199	200	∞	1291.29	1564.36	27%	0.0196
6_50	50	160	200	555.43	911.921	64%	0.0014
7_75	75	140	160	909.68	2044.30	125%	0.0027
8_100	100	200	230	865.94	1438.11	66%	0.0052
9_150	150	200	200	1162.55	2428.42	109%	0.0112
10_199	199	200	200	1395.85	2803.7	101%	0.0206

Table 3.4-4 Initial solutions generated using the Sweep algorithm in a clockwise procedure

Name	Customer Size	Capacity	Max Route Length	BKS	Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	667.244	32%	0.0014
2_75	75	140	∞	835.26	932.712	12%	0.0027
3_100	100	200	∞	826.14	952.194	17%	0.0071
4_150	150	200	∞	1028.42	1161.7	19%	0.0145
5_199	199	200	∞	1291.29	1556.63	30%	0.0245
6_50	50	160	200	524.61	844.91	52%	0.0013
7_75	75	140	160	835.26	2030.69	123%	0.0027
8_100	100	200	230	826.14	1366.35	58%	0.0052
9_150	150	200	200	1028.42	2362.53	103%	0.0115
10_199	199	200	200	1291.29	2835.6	103%	0.0207

Table 3.4-5 Initial solutions generated using the Clarke and Wright Savings algorithm in a sequential procedure.

Name	Customer Size	Capacity	Max Route Length	BKS	Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	584.637	11%	0.0025
2_75	75	140	∞	835.26	905.306	8%	0.0058
3_100	100	200	∞	826.14	893.912	8%	0.0115
4_150	150	200	∞	1028.42	1134.83	10%	0.0287
5_199	199	200	∞	1291.29	1424.29	10%	0.0589
6_50	50	160	200	524.61	607.947	16%	0.0024
7_75	75	140	160	835.26	1525.2	83%	0.0064
8_100	100	200	230	826.14	971.42	18%	0.0111
9_150	150	200	200	1028.42	1327.67	29%	0.0310
10_199	199	200	200	1291.29	1546.23	20%	0.0604

Our results show that on small size instances <199 customers the preferred initial solution method is the Clarke and Wright Savings algorithm. Although, in terms of computation time the Sweep algorithm out performs the Clarke and Wright by a factor of 2, although both of these times are very small and so the difference is negligible. The Clarke and Wright solutions produce reasonable solution results considering the simplicity of the model. The large deviations from the BKS occurred when a service time constraint was added. Notably the sweep algorithms performed very poorly in these cases with occasionally providing initial solutions 100% away from the BKS.

3.4.2 Local Search Improvement Methods & Capacity Change

After the initial search phases various improvement methods can be used for each initial solution (anticlockwise sweep and clockwise sweep) in order to further improve the solution quality, this is our step 2. These include Inter-Route shifts, swaps and moves, 2-opt & 3-opt exchange as well as the Intra-Route heuristic. At each improvement method the overall best solution is chosen to move onto the next improvement technique. The process was implemented in an iterative process, taking the improved solution from each improvement into the next method. Once one cycle has been completed the best result is then taken back through the improvements techniques; this continues until the solution can pass through all the improvement techniques without an improvement. Figure 3.4.4. Provides a flowchart diagram enabling the reader to easily see how each step are linked and the process involved at each stage. After each of the local search operators are used Intra-route is used to further optimise the solution. As you can see the swap and move operators feed into each other iteratively, while this does provide good quality solutions it must be noted that occasionally the solution get stuck in a local optimum. There is another variation of this operation whereby at each step the solution is fed back into the 1-0 / 0-1 local search operator, the process will be further discussed later and can be seen in figure 3.4.9. After these initial solutions improvement procedures were used to further improve on the achieved solutions. The improvement procedure utilises a neighbourhood structure based on shift and swap moves. These moves include the swap intra-route, (1-0) - (0-1) shift, the (1-1) swap, the (2-0) - (0-2) shift, (2-1) move, the (2-2) swap, the 2-opt and 3-opt.

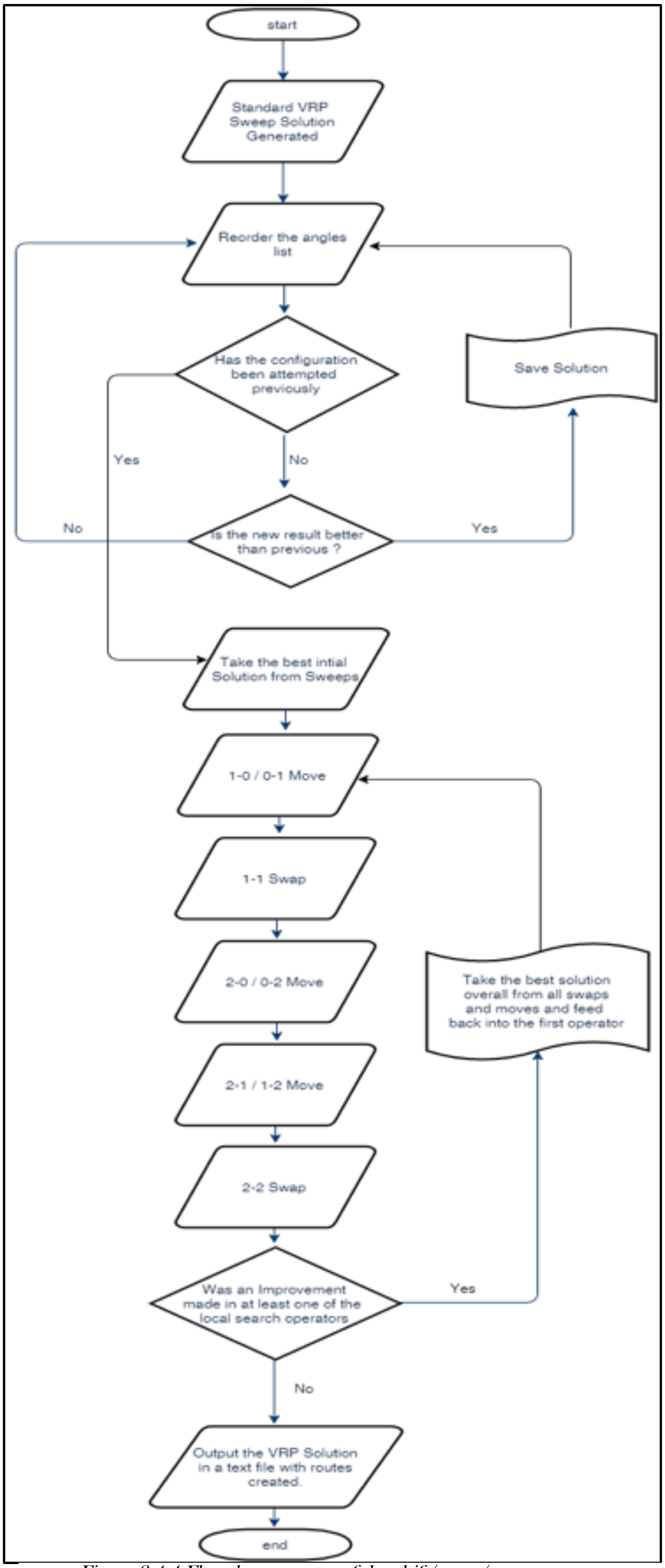


Figure 3.4.4 Flowchart process of the shift/move/swap operators

Here after each operator the solution is fed back into the first operator and then passed through the other operators. The second improvement procedure that was tested is to be referred to as the cyclic improvement method. Here the solution passes through all the operators (same order as in the iterative method) and if there is an improvement then the best current solution is fed back into the first move – the (1-0)-(0-1) shift operator. The best solution from the (1-0)-(0-1) shift is then used in the initial (1-1) swap. This then continues through the other operators (2-0)-(0-2) shift, (2-1) move and (2-2) swap. Once the solution has passed through them all the best result is then fed back into the (1-0)-(0-1) shift and the cycle is repeated. This is continued until no further improvements were made in any local search operator. Figure 3.4.5 shows the cyclic improvement method visually.

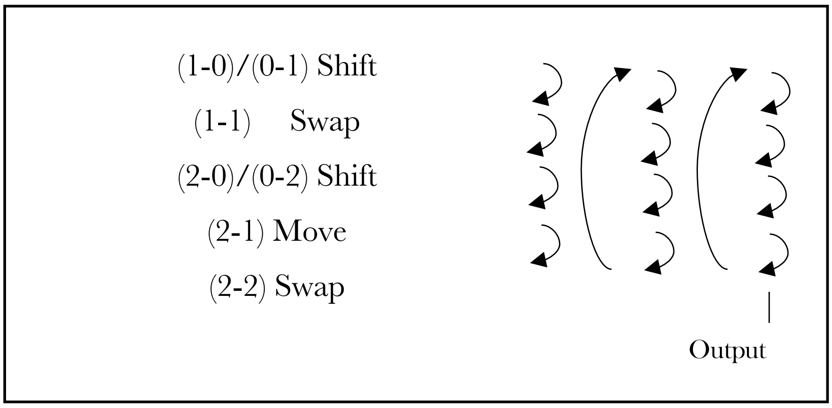


Figure 3.4.5 The Cyclic Improvement Method

The 1-0 and 0-1 move is a technique involves removing the first member of the first route and inserting in at the first member of the second route, if no capacity constraints or max route constraints are broken the new solution is calculated and saved if the solution is better than the previous best then this is saved as the new best. The original solution from the sweep solution is then used again and the first member of the first route is removed and inserted into the second member in the second route, again the route is saved if a new best is found. This method is continued inserting the first member of the first route into each position within the second route. Figure 3.4.6 demonstrates the 1-0 shift moving a customer from a route into another route.

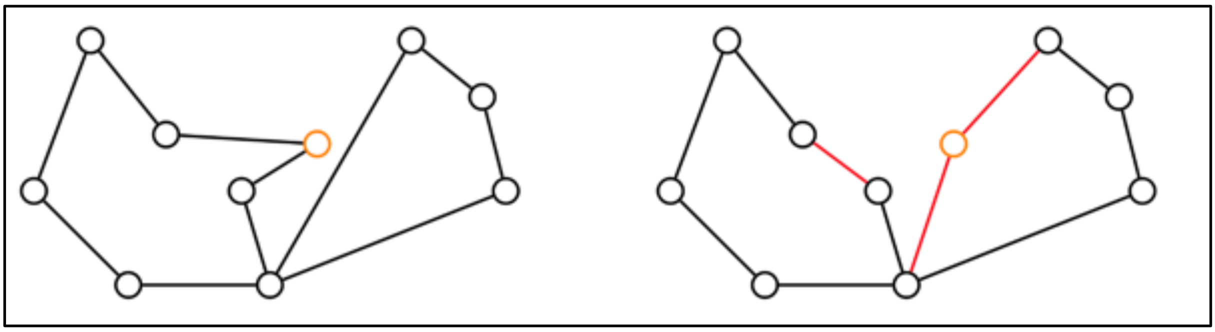


Figure 3.4.6 Demonstrating the 1-0 move using diagrams from Laporte and Semet (2002).

After this the process then moves onto inserting the first customer into the third route at each position. One the first member of the first route has been inserted into each position of each route the method then chooses a new customer to be inserted this is the second member of the first route, the whole process is again repeated inserting the customer into the first member of the second route etc. Once each of the customers within the first route has been inserted into each position within each other routes the algorithm then moves onto the next route and begins by removing the first member of route 2 into the first position of route 1. The algorithm cycles through all the members of each route, removing the customer and inserting them into other routes. Once the best has been found the method then runs again with the new solution, this method continues until the shift 1-0 / 0-1 can be completed with no further improvements. The overall best solution is then taken, and the next operator technique is used. In this case this is the 1-1 swap.

The swap 1-1 looks at swapping positions within two routes, firstly the first member of the first route is switched with the first member of route 2, if no capacity constraints or max route constraints are broken the new solution is calculated, if the solution is better than before the solution is saved as the overall best. The best solution from the previous technique is used and

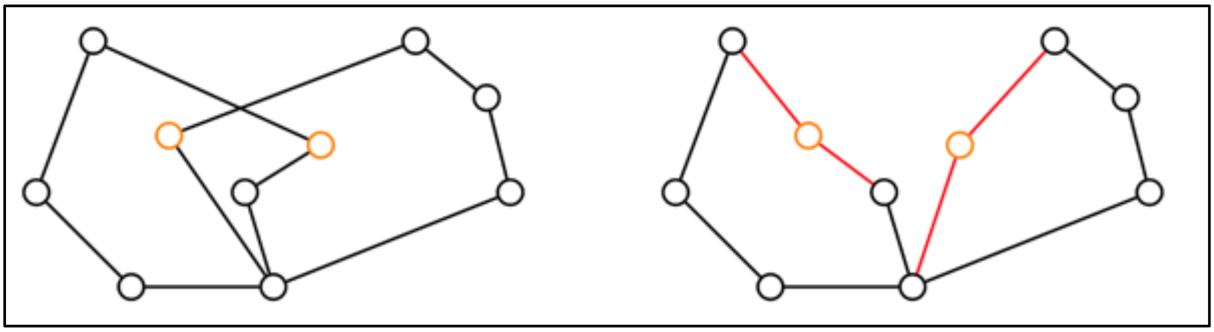


Figure 3.4.7 Demonstrating the 1-1 swap using diagrams from Laporte and Semet (2002).

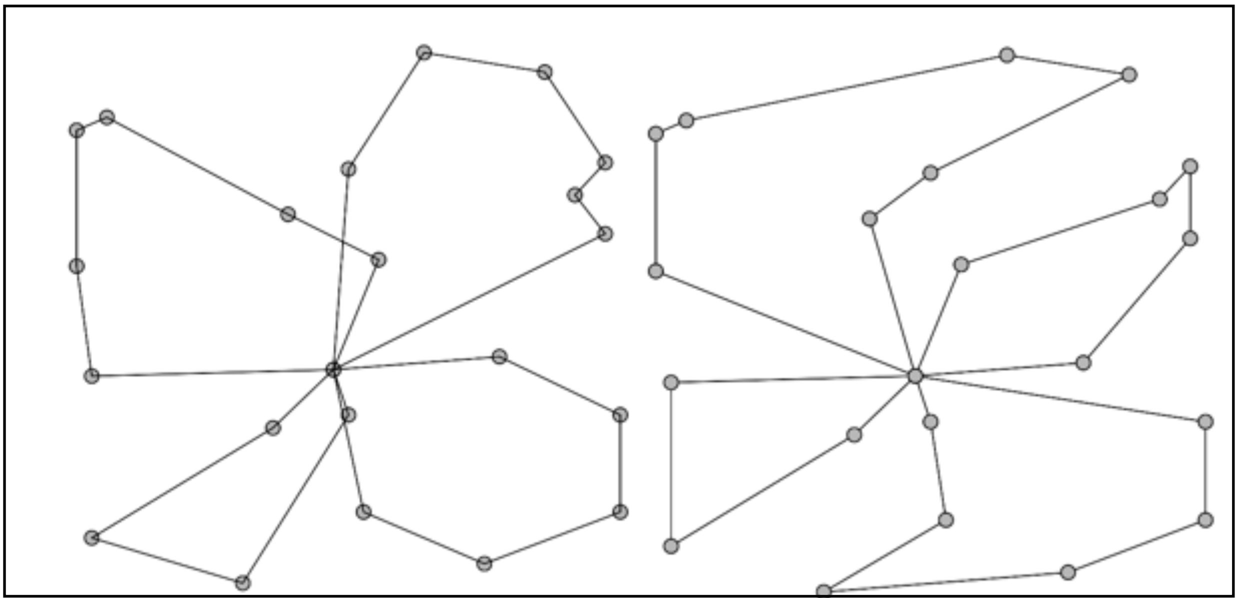
the swap 1-1 now moves to switch the first member of route 1 with the second member of route 2 and again solution saved if it is better than the previous overall best. Figure 3.4.7 shows how this swap is implemented swapping the first member of a route with the second member of another route. Once the first member of the first route has switched positions with every other member in each route the algorithm moves onto the next member in route 1, this continues with each customer of every route.

Once the swap 1-1 has completed the overall best is saved as current best and then the next operator technique is used, this is the 2-0 / 0-2 shift.

The shift 2-0 / 0-2 shift is the similar to the 1-0 / 0-1 shift except instead of removing and inserting 1 customer at a time 2 customers are removed and inserted together. This algorithm takes two customers adjacent to each other and tries inserting them into the next route still next to each other. Once each pair customers have been inserted into every position in every route the best solution is chosen and saved as the overall best and then taken into the next operator technique Move 2-1.

The move 2-1 / 1-2 is again another variation of the shift 1-0 operator however here at each point 2 adjacent customers are switched with 1 from another route. The single customer that is switched with the 2 is cycled through all the positions of every route the 2 adjacent customers that are to be inserted/swapped are then moved to the next customers in the first route.

The Swap 2-2 is same as swap 1-1 except 2 adjacent customers are moved together simultaneously. This operator can cause large changes within the route structure and helps advance the solution into other neighbourhoods.



Anticlockwise Sweep Solution using the best starting position with Intra-Route and all improvement heuristics described. Solution = 375.28 (Optimal within Literature) 4 Routes, 93.75% Tightness

Clockwise Sweep Solution using the best starting position with Intra-Route and all improvement heuristics described. Solution = 383.5, 4 Routes, 93.75% Tightness.

Figure 3.4.8 Results generated from Anticlockwise and Clockwise Initial solutions, using improvement techniques.

After each swap iterator the Intra-Route algorithm is used to optimise each route individually functioning as described previously. When testing the improvement techniques optimal solutions were found for the Christofides 21 dataset that was used for testing.

The final outputs for each initial solution (anticlockwise and clockwise) can be seen in Figure 3.4.8. The result generated using the anticlockwise sweep initial solution allowed the improvement techniques to generate the optimal solution for this dataset. Although after the initial solution the clockwise method generated the better result, however, the shift/move/swap operators couldn't improve the solution beyond 383.5 as it was probable it got stuck in a local optimum.

Further investigation into the way these operators function was required and so the order in which they are called was chosen to be altered to investigate how it effects solution quality. Figure 3.4.9, shows how these shift/swap/move operators were manipulated to operate at different times, where the previous method works on an iterative basis whereby each shift/swap/move operator is fed into the next, the process shown in Figure 3.4.10 is a modified iterative process.

Tables 10-14 demonstrate the effectiveness of the chosen improvement heuristics and the way the different improvement method effect the result, and also show the role the two initial solution methods have on the objective value. Two datasets were chosen problem size instances ranging from 50 -199 are instances from Christofides et al. (1979) and problem size instances ranging from 240 -480 are instances from Golden (1998).

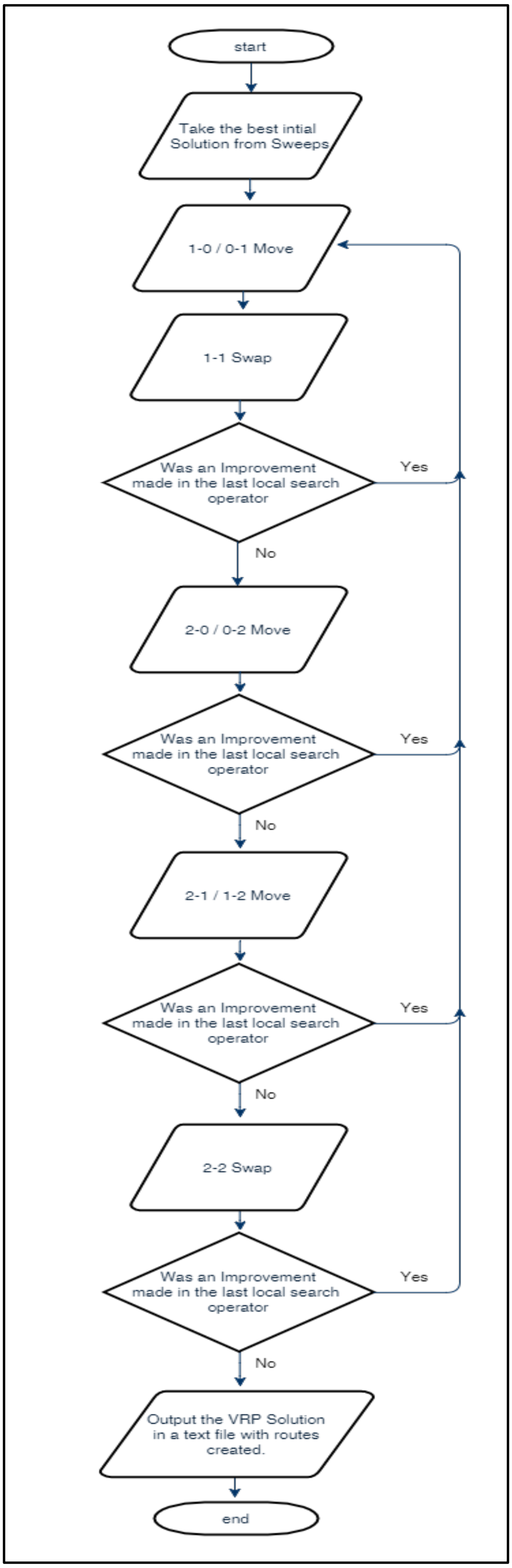


Figure 3.4.9 An alteration to the iterative shift/swap/move operators

This process is performed in an iterative way; at each stage the best solution is then fed back into the first of the improvement moves, the (1-0)-(0-1) shift. After each local search improvement was made the 2-opt and 3-opt heuristic was used to further improve on the best solution. Once each local search improvement has been implemented the result is then outputted. The iterative improvement method is shown in Figure 3.4.10.

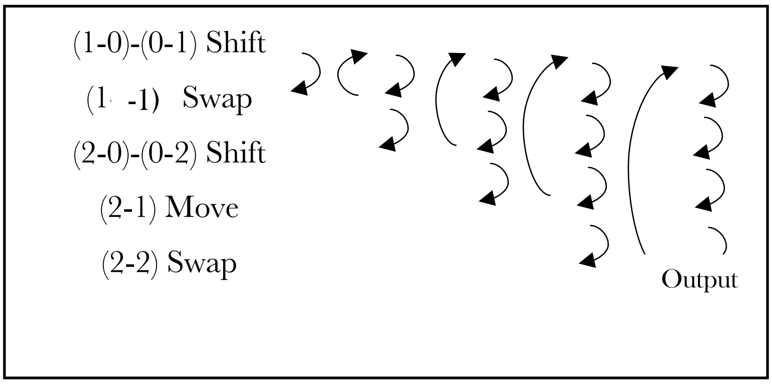


Figure 3.4.10 The Iterative Improvement Method

The iterative improvement method feeds the best solution found at each stage back into the first of the operators. i.e once the (1-1) swap solution has found the best current solution this best current solution is then the global best and then the (1-0)-(0-1) shift operator uses this as a starting point. Both methods provide new ways at manipulating local search methods to further improve their solution space search.

To further diversify the neighbourhoods and have the ability of further improving the solution a capacity constraint change was implemented at the end of each output. The best solution along with the best matrix was saved globally allowing the program to be run again (this time with a reduced initial capacity allowance) and the new solution compared to the previous. In our tests for the Christofides et al. (1979) the maximum reduction in vehicle capacity was found to be effective up to 80% of the capacity limit and a reduction of up to 60% of the capcity limit in the Golden et al. (1998) instances, it was found to be effective for one particular instance, namely the 2_320. This is due to the quality of the initial solutions produced. It was found that the quality of the initial solutions when using the Golden et al. (1998) instances was very poor and averaged 150% deviation from the best-known solution.

In order to analyse the change in capacity constraint and test whether a reduction in initial capacity constraint can benefit solutions, computational runs were carried out reducing the capacity by 1% each iteration. The final results for 4 datasets of the varying capacity constraint can be seen in Figure 3.4.11.

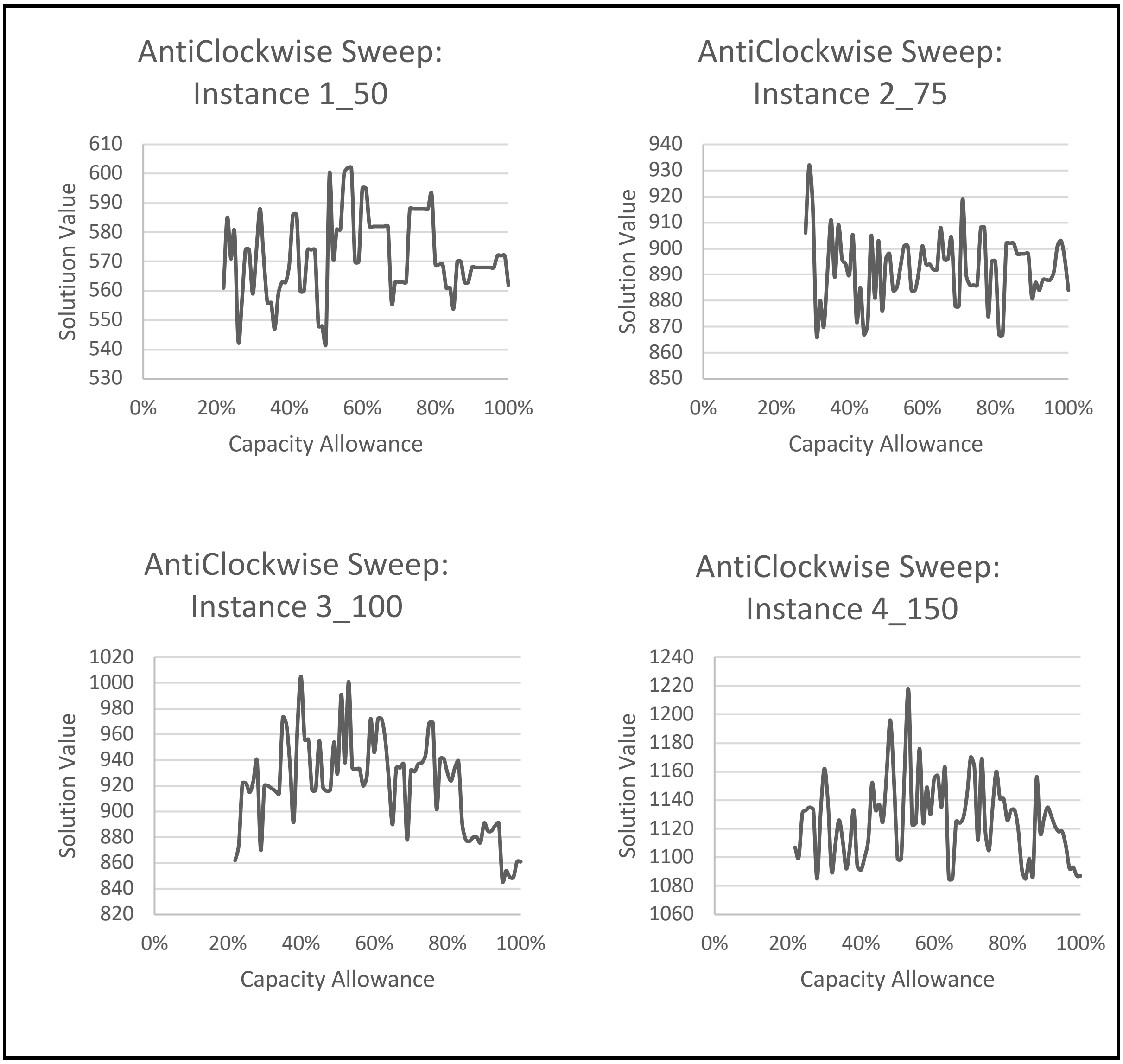


Figure 3.4.11 Graphical comparison of how a reduction in capacity of the initial solution effects the final solution value.

The results displayed in Figure 3.4.11 highlight the influence this reduction in capacity can be in terms of solution value. While no specific starting capacity constraint provided better results than the rest, the best solution value can be found at different capacity allowances for the various instances. There is no notable pattern as to when these best results occur, within the 1_50 and 2_75 instances this value occurs at around a 30% capacity allowance, instance 3_100 provides the best result when capacity allowance is 95% and instance 4_150 delivers best values at 67% and 85% capacity allowance. Due to the range of values at which the best value is obtained it can therefore be said that there should be no fixed capacity reduction percentage used. By altering the initial starting capacity our test results allow us to achieve a greater spread of neighbourhoods and ultimately a better chance of discovering a better solution. In order to achieve optimal results a wide range of capacity constraints need to be tested. While this can yield better solutions, the run time is heavily extended proportionally to the number of runs tested. For the remainder of this thesis the maximum capacity allowance used for the Christofides et al. instances will be set to the lowest capacity allowance percentage, this value is found by identifying the maximum demand of a single customer i within the dataset and dividing by the maximum vehicle capacity for that instance. The results and cpu time shown are those of the best capacity constraint. The following results presented in Tables 3.4-6, 3.4-7, 3.4-8, 3.4-9 and 3.4-10 are the results from allowing multiple runs with the capacity changing at each initial solution.

Table 3.4-6 Christofides et al. results from the cyclic procedure method using the anticlockwise sweep initial solution

Name	Customer Size	Capacity	Max Route Length	BKS	Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	551.53	5.1%	0.14
2_75	75	140	∞	835.26	867.15	3.8%	0.25
3_100	100	200	∞	826.14	846.44	2.5%	0.71
4_150	150	200	∞	1028.42	1085.53	5.6%	2.34
5_199	199	200	∞	1291.29	1370.99	6.2%	6.23

Table 3.4-7 Christofides et al. results from the cyclic procedure method using the clockwise sweep initial solution

Name	Customer Size	Capacity	Max Route Length	BKS	Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	537.37	2.4%	0.12
2_75	75	140	∞	835.26	863.99	3.4%	0.26
3_100	100	200	∞	826.14	844.96	2.3%	0.77
4_150	150	200	∞	1028.42	1064.97	3.6%	2.62
5_199	199	200	∞	1291.29	1367.26	5.9%	6.01

Table 3.4-8 Christofides et al. results from the iterative procedure method using the anticlockwise sweep initial solution

Name	Customer Size	Capacity	Max Route Length	BKS	Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	551.53	5.1%	0.10
2_75	75	140	∞	835.26	857.53	2.7%	0.20
3_100	100	200	∞	826.14	847.72	2.6%	0.65
4_150	150	200	∞	1028.42	1072.35	4.3%	1.74
5_199	199	200	∞	1291.29	1372.10	6.3%	6.03

Table 3.4-9 Christofides et al. results from the iterative procedure method using the clockwise sweep initial solution

Name	Customer Size	Capacity	Max Route Length	BKS	Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	547.86	4.4%	0.14
2_75	75	140	∞	835.26	865.13	3.6%	0.20
3_100	100	200	∞	826.14	845.72	2.4%	0.70
4_150	150	200	∞	1028.42	1074.01	4.4%	2.04
5_199	199	200	∞	1291.29	1383.12	7.1%	6.21

Table 3.4-10 Christofides et al. results from the cyclic procedure method using the Clarke and Wright initial solution

Name	Customer Size	Capacity	Max Route Length	BKS	Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	529.976	1.0%	0.41
2_75	75	140	∞	835.26	851.215	1.9%	0.66
3_100	100	200	∞	826.14	838.532	1.5%	0.98
4_150	150	200	∞	1028.42	1075.54	4.6%	3.10
5_199	199	200	∞	1291.29	1369.57	6.1%	9.41

The results shown in Tables 3.4-6, 3.4-7 and 3.4-10 are when the local search improvement moves are performed using the cyclic improvement method. On average this cyclic improvement method performed 0.5% better than the iterative method shown in Tables 3.4-8 and 3.4-9 with lower computational times. Overall the best results occurred when the Clarke and Wright initial solution was combined with the cyclic method, these results showed an average of 1% and 1.2% improvement over the Sweep initial solutions with Cyclic method and with Iterative method respectively. We believe this is due to the better initial solutions generated using the Savings algorithm over sweep. The solutions values provide better results for specific instances rather than an overall change with the majority of improvement over the sweep results occurring in smaller instances. With the larger problems from the Christofides et al. datasets (150+ customers) better quality solutions were found with the Sweep clockwise initial solution combined with the cyclic method. Computational running times for both the iterative and the cyclic methods using Sweep as an initial starting solution were significantly lower when compared to the Clarke and Wright with the cyclic method.

Table 3.4-10 shows the results of the Clarke and wright savings heuristic when the cyclic improvement method is used. The results achieved here are the best in terms of solution quality of the 5 methods, with the exception to instances 4_150 and 5_199. A slight increase in time was seen although this is minor. Our results again demonstrate the ability of the Clarke and Wright method with good quality solutions in a reasonable amount of time.

Research on the development of heuristics of the VRP has been heavily covered within literature although it is not known to the best of our knowledge of a study which analyses the effect that varying the capacity constraint has on the solution value. The most powerful method proposed here performed well in small and medium instances (<200 customers) solving the problem close to the best-known solutions. The change in capacity helped improve the solution quality although the increase in computational time running up to 80 iterations (80% reduction in capacity constraint in 1% steps) is costly. The CPU times on the whole are very fast with small and medium instances, however in larger sized problems (>250 customers) the algorithms lose solution quality. Metaheuristics are suggested in order to provide better quality solutions in a more reasonable time. By varying the initial neighbourhoods this method is comparable to that of the VNS. Utilising the same local search functions as the VNS, however instead of the shaking method we instead reduce the capacity constraint of the problem forcing the algorithm to produce a new neighbourhood. This additional capacity constraint is then relaxed for the local searches allowing additional local search moves escaping local minima's in terms of solutions.
The VNS was chosen due to its power and ability to generate numerous neighbourhoods quickly and efficiently. These traits suit the platooning problem that is discussed in the next chapter as it allows more potential platoons to be formed. The VNS algorithm that was used in this thesis is presented below and also is presented in Psuedocode for ease of reading in Appendix 2.

1. Set up starting parameters and matrices setting the current best to the initial solution – VNS and local matrix = initial matrix.

2. Set a counter to 0 e.g k=0 and create a loop where k=k+1

3. Setting the global improvement factor to false, if a local search routine improves the current solution then set this global improvement to positive and update the best global matrix to the best solution. Continue until no global improvement is achieved once all local searches have been completed.

4. Run local searches including shift (2-0), two-opt and three-opt, insert (1-0) and (2-1) and swap (1-1) and (2-2), each improvement that is found and made update the VNS matrix with this new best result.

5. Perform VNS shaking where a random customer from a random route will be inserted into a new route.

6. Start the local searches again with the new starting solution and repeat local searches while k is less than k limit e.g k<50.

7. Once k limit is reached, output the best current route matrix, perform a two opt and three opt and output file for graphical representation. Then calculate total CO_2 produced from result.

Table 3.4-11 VNS Results on the Christofides et al. benchmark datasets

Name	Customer Size	Capacity	Max Route Length	BKS	VNS Objective	% Deviation from BKS	CPU time (s)
1_50	50	160	∞	524.61	527.029	0.5	1.79
2_75	75	140	∞	835.26	845.294	1.2	5.97
3_100	100	200	∞	826.14	839.488	1.6	13.49
4_150	150	200	∞	1028.42	1061.91	3.3	135
5_199	199	200	∞	1291.29	1344.16	4.1	242
6_50	50	160	200	555.43	569.243	2.5	2.97
7_75	75	140	160	909.68	1044.66	14.8	7.0
8_100	100	200	230	865.94	923.84	6.7	20.3
9_150	150	200	200	1162.55	1290.43	11.0	127
10_199	199	200	200	1395.85	1501.5	7.6	91.0
11_120	120	200	∞	1042.11	1050.4	0.8	45.6
12_100	100	200	∞	819.56	821.52	0.2	18.4

Table 3.4-11 shows the computational results for the Christofides et al. benchmark datasets when implementing the VNS. The model uses a basic variable neighbourhood search algorithm with a stopping procedure. The results shown in Table 3.4-11 provide accurate solutions close to the best-known solutions within literature however they have a fairly long computational time. This computational time was on average 50 times that of the results shown in Tables 3.4-6 - 3.4-10 where a no shaking occurred, or, in this instance no capacity change at the end of each iteration The VNS based heuristic was used to find a reasonable feasible solution to the CVRP and has shown that it is working correctly although not as efficiently as expected. It is suspected that the VNS shaking method is not shaking the neighbourhood enough and allowing the result to drop back into its local optimum. In future research this is advised to be investigated further with stricter capacity changes to further shake the neighbourhoods.

3.4.3 CO_2 Calculation and Experiment

Once a good quality solution has been found the emissions are calculated. This provides the user a base level on which to improve upon. This step is added to provide the reader with insights into how the VRP is used to improve the efficiency of routing with real world effects. The aim is to identify the environmental impact of each solution using emission values. In order to see the impact that each of these solutions have on the environment, the results need to be converted to be able to produce a CO2 value. The CO2 calculation takes into consideration the load of each arc of the solution. This step is also crucial when identifying the benefits platooning can bring to a road transport system. As fuel consumption is directly related to CO_2produced this is calculated accurately and then converted into a final CO_2 value. Platooning due to its nature may increase the distance of the solution model, however the CO_2 may decrease to increased fuel economy. It is therefore important that an accurate emissions model is created to help identify the benefits platooning can produce. The following experiment was conducted over the period of Covid-19 as such, the limited access and the time constraints meant that the data was not able to be used within the models of this thesis. The results from this experiment now provide valuable data for the reader and future researchers, improving the accuracy of consumption models within routing.

In order to accurately calculate the CO2 of a vehicle while travelling along each route then real-life data on how vehicles react to speed, gradient and load needs to be taken into account. Based on common knowledge of vehicle mechanics, various forces can be calculated for vehicles with changing speeds, road gradients and load. These forces can then be simulated on a chassis dynometer, the vehicles fuel consumption is then outputted providing accurate data for researchers to then feed into their models to improve consumption modelling. The experiment begins with a few assumptions and calculations. Three vehicles were tested the first a 2016 Vauxhall Combo van, for the sake of this experiment this is considered a small van. The engine in this particular model is a 1.6l inline 4-cylinder diesel engine producing 104bhp. The van has a mass of 1410kg a frontal area (A_f) of 2.58m^2 and a drag coefficient (c_d) of 0.35 (The Engineering Toolbox 2021). The second van was a 2016 Citroen Dispatch, this is considered a medium van for our experiment. The engine is a 1.6l inline 4-cylinder diesel engine producing 94bhp. The van has a mass of 1900kg, A_f of 4.3m^2 and a c_d of 0.35. The last vehicle tested was a 2018 LWB Peugeot Boxer Van considered a large van with a 2.0l inline 4 cylinder diesel engine producing 128bhp. The Boxer van has a mass of 2060kg, A_f of 4.6m^2 and a c_d of 0.4. The rolling resistance constant f_{rl} is constant for all the vans due to the similar tyres and road surface and is considered to be 0.015. Data can be found at The Engineering Toolbox (2021). A set of speeds was chosen to best simulate real speeds achieved when driving on UK roads, with speeds over the national speed limit included to provide the reader with a deeper understanding of the effect speed has on fuel consumption. The speeds begin at 16km/h and continue in 16km/h increments up to a maximum of 128km/h. The chosen gradients were 0°, 1°, 2° and 5°, these gradients were chosen to provide a good range of gradients that are found in real-life, for the sake of this experiment we only considered either flat ground or inclined, in future research it would also be possible to conduct this experiment with negative gradients. Four loads were simulated, no load, 100kg, 200kg and 500kg. These loads were chosen for the experiment as it is a reasonable amount of weight to be transported in all of the vehicle types tested. Using the data and the assumptions we have made we can calculate the required resistive force for the vehicle to achieve its target speed. We start by identifying what these resistive forces are for each vehicle. The instantaneous power of a vehicle is determined by vehicle speed, acceleration and the gradient. From basic physics the required tractive effort for all vehicles can be described using three major resistances:

$$F = ma + R_a + R_{rl} + R_g \tag{1}$$

Where F is the tractive effort (in N), m is the vehicle mass (in kg), a is the acceleration (in m/s^2) and R_a, R_{rl} and R_g are the aerodynamic, rolling and grade resistances respectively (in N). R_a, R_{rl} and R_g can be calculated in the following equations:

$$\begin{cases} R_a = kv^2 = \frac{\rho}{2} C_D A_f v^2 \\ R_{rl} = f_{rl} mg \\ R_g = mgsin\theta \end{cases} \tag{2}$$

Where k is the aerodynamic resistance constant, determined by air density ρ (in kg/m^3), coefficient of drag is C_D and the frontal area of the vehicle is given by A_f (in m^2). f_{rl} is the rolling resistance constant and g is the acceleration of gravity (g = 9.81 m/s^2). Combining Equations (1) and (2) above provides:

$$F = ma + kv^2 + f_{rl}mg + mgsin\theta \tag{3}$$

For our experiment the vehicles were held at steady velocities and force while the fuel consumption was measured. Therefore, the acceleration is zero. The constants ρ and g have values 1.23kg/m^3 and 9.81 m/s^2 respectively. Using the chassis dynometer we can output the force the vehicle exerts on the dyno and match it with our calculated values while measuring the equivalent MPG. Figure shows the chassis dynometer in use, a Maha MSR500. The vehicle is strapped down in place and is driven as normal on the rollers. The chassis dynometer provides a safe and consistent testing bed ideal for simulating roads.

Figure .3.4.12 The Maha MSR500 Chassis Dynometer in use.

Using this method, we can simulate various loads with the associated change in fuel consumption. The full results can be found in Appendix 4, here all the simulated forces can be seen along with the measured MPG's. Please note that within these results some of the MPG values have a ## symbol, this is to denote when the vehicle failed to achieve the require target force. For ease of viewing, figures 3.4.13 and 3.4.14 provide a graphical representation of the results in the two most extreme cases of a small van with no load and with 500kg of load respectively.

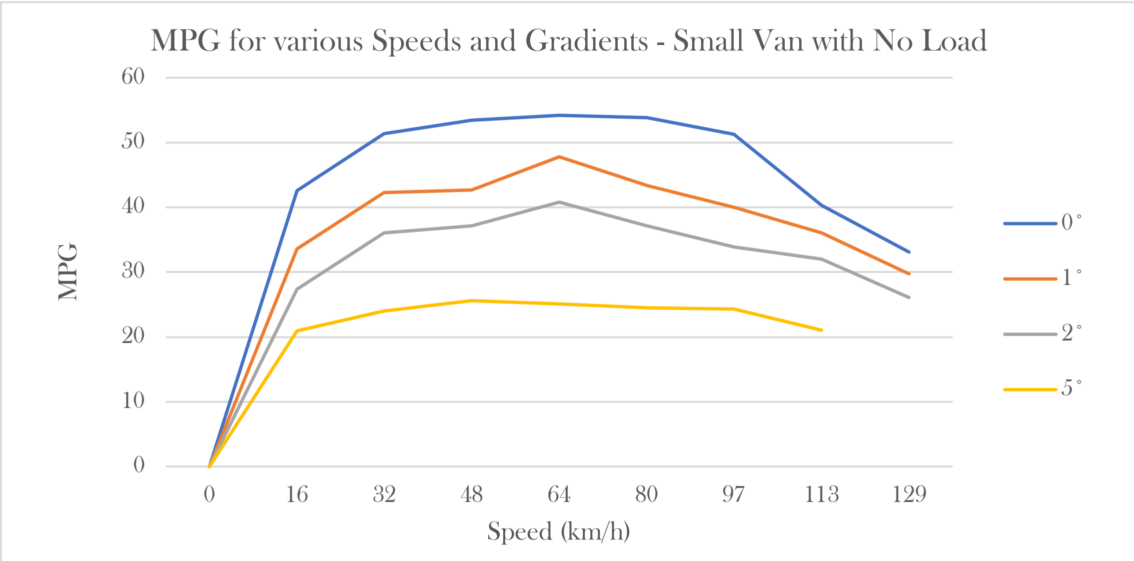


Figure 3.4.13 Graph displaying the associated MPG for a given gradient and speed of a small van with no load.

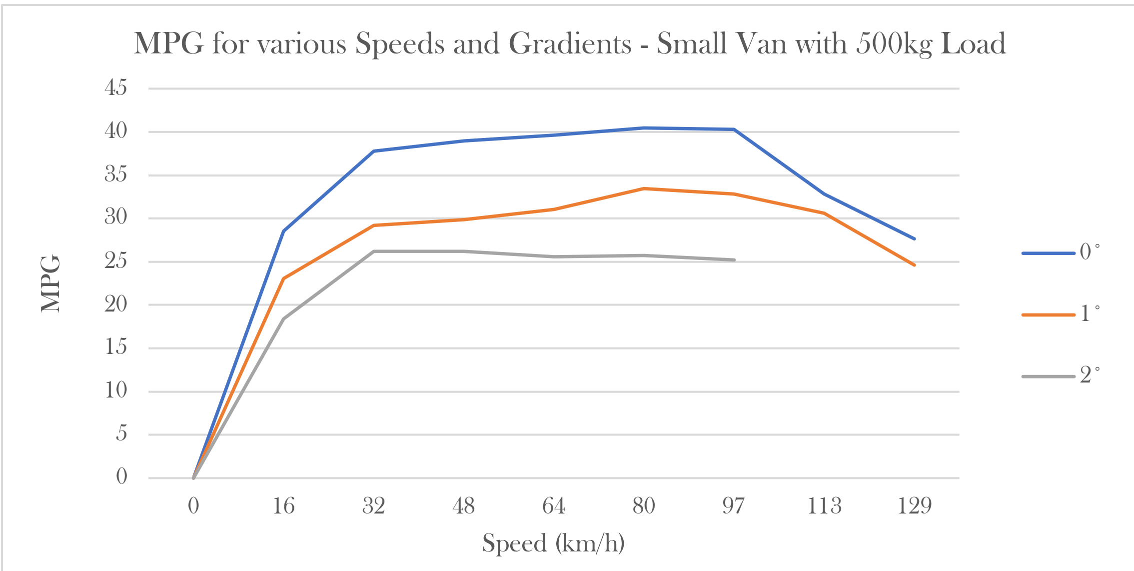


Figure 3.4.14 Graph displaying the associated MPG for a given gradient and speed of a small van with 500kg load.

The figures clearly show the drop in MPG and the increase in fuel consumption. A drop of 15MPG can be seen at 64km/h with no gradient when comparing the no load to 500kg. The small van shown in these figures generally improves MPG as speed increases up until 80km/h after which time the MPG increases. This is due to the increase in aerodynamic resistance, getting exponentially larger as speed increases. The change of load in the vehicles also alters these ideal speeds, it can be seen that at heavy loads a slower speed is preferable as gradient increases.

Due to time constraints the algorithms used in this thesis did not include the CO_2 experiment data found. Instead, several assumptions were made when calculating the initial CO2 value in the instances shown in this thesis. Although, the CO_2 experiment conducted above was not conducted in vain. It is hoped to add additional knowledge to research aiding and providing future research the critical data to improve accuracy when calculating fuel economy and ultimately emissions when developing routing algorithms. The first assumption was a constant average speed along each of the routes 50mph, a constant flat gradient, an empty vehicle weight of 2200kg. While the vehicle was empty and meeting the first two assumptions the miles per gallon of the empty vehicle was 25mpg during testing. The vehicle tested was a Mercedes Vito as seen in figure 3.4.12 Similar to the CO_2 experiment conducted the real-life tests were performed in a closed environment on a rolling road. Using the force equation above, calculating the required force for our assumptions i.e to maintain a constant 50mph at zero gradient with our relevant vehicles frontal area, drag and rolling resistances we can calculate the required force for varying weights of the vehicle. Again, using the chassis dynometer a constant force is held on the rollers allowing us to read the vehicles outputted mpg through the vehicles instrument cluster and then alter this force for the next simulated weight. This provides a mpg value to be calculated for different theoretical vehicle loads. The values that were created at a speed of 50mph and the values achieved are shown in Table 3.4-12.

Table 3.4-12. Results produced after testing a Mercedes Vito Van in a closed testing facility using a rolling road.

Simulated Vehicle Load (kg)	MPG
2400	24.5
2600	23.5
2800	22.5
3000	21.5

These values for MPG and load follow a linear pattern, for the following calculations we assume this to be the case at higher and lower vehicle loads. We can then use linear regression to create a regression equation to be applied within the model to generate estimated values of MPG using varying loads of vehicles. The linear regression equation to calculate MPG used in the algorithm is as follows:

$$MPG = (-0.005 * (Vehicle\ Weight + (Total\ Load)) + 36.5 \qquad (4)$$

The value of -0.005 represents the gradient of the linear regression equation and 36.5 is error term and not directly observed. Once the best solutions were found, the CO2 calculation was then implemented. Starting with the first route the first customer is selected and the MPG is calculated using equation 4 and also equation 5 below to calculate the load of goods on the vehicle.

$$w_{jm} = (q_n - \sum_{i=1}^{m} q_i) \qquad (5)$$

Where w_{jm} is the weight of the vehicle's j load after having visited the first m customers, n is the total number of nodes/customers along route j,$q_n$is the total load for all nodes/customers and q_i is the load for node/customer i. Effectively the vehicles load equates to the total tour demand minus the total demand that has been served to customers on that route. The calculated MPG's were assigned to their respective routes enabling the amount of fuel used in Gallons per arc of each route to be calculated.

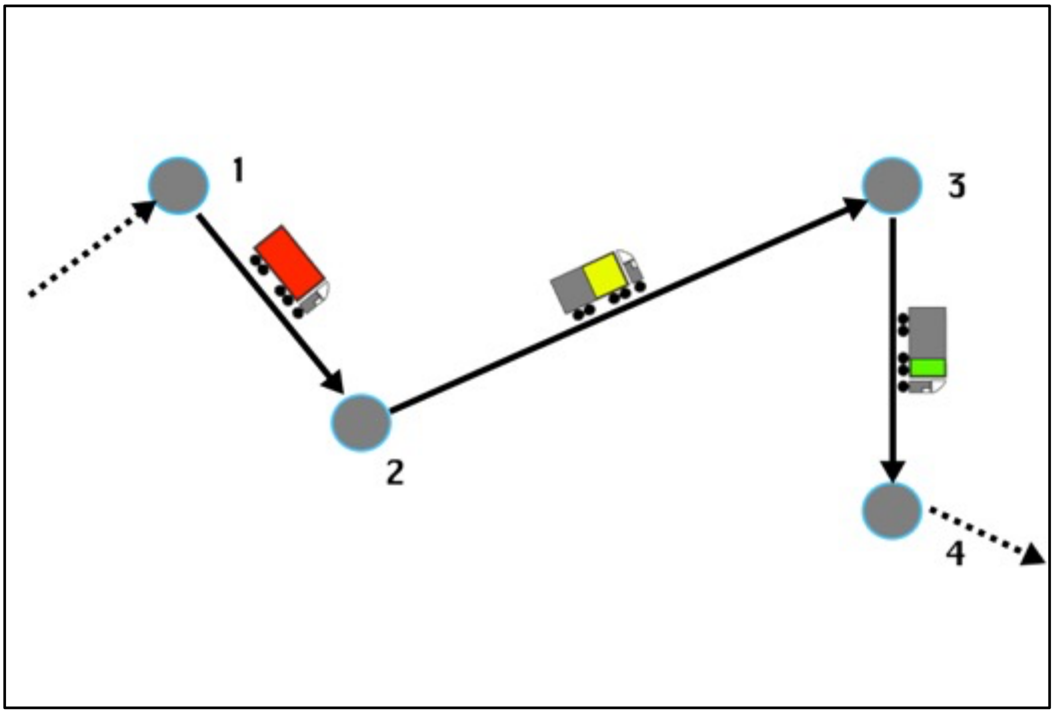


Figure 3.4.15. A Vehicle Route with customer's goods being unloaded at the respective location.

Figure 3.4-15. demonstrates a section of a vehicle's route traversing several arcs between customers. Travelling from customer 1 to customer 2 the vehicle is heavily loaded (shown in red) during this section of the route the vehicle will have its worst fuel efficiency, and the lowest MPG. The next section of the route from customer 2 to customer 3 will have slightly better fuel efficiency as the vehicle has unloaded some of its goods to customer 2, and evidently an increase in MPG will be achieved. Once the MPG of each arc of the route is known then it is a simple case of multiplying the length of each arc with its relevant MPG, in order to find the arcs fuel usage in gallons. Summing all the arcs together provides the total fuel consumption of the vehicles route. Using data from the US energy administration (2016) it can be assumed that 10.172kg of CO2 is produced per Gallon of Diesel burned. Using this information, the total fuel used is converted into total CO2 produced. When calculated, the amount of CO2 produced for the optimal Anticlockwise Sweep solution generated when testing (figure 3.4-8) amounted 153.059kg and the Clockwise solution produced 156.416kg of CO2. This emissions calculation is now taken further and applied within the platooning model directly and can be adapted to include speed as a function as an extension.

3.4.4 Basic Platooning model

Step 4 is when we employ our platooning algorithm. Our basic platoon model is tested on the current solution and if the emissions of the new platoon route is less than that of step 3 it is accepted. This basic method strictly allows splitting points at current customer locations only. In the following instances we consider only the first arcs of each route in these instances for simplicity. Although, there is no reason why this model cannot be extended further to include more platooning options at other points along a vehicles route.

Step 4 of our Platooning Algorithm can be further broken down as follows:

- Look for common routes to merge using the initial arcs of each of the routes from the VRP solution.
- Find two routes to merge based on their customer distances.
- Find a good splitting point x.
- Calculate new distance from depot to x and from x to each respective next customer for both vehicles.
- Starting with the common arc (depot to x), choose lead and tow vehicle, lead receives 6% reduction in fuel consumption, tow receives a 21% in fuel consumption reduction. Choice is based from largest savings on MPG calculation for that arc prior.
- Calculate new CO_2 levels for new routes and accept if better.

In order for platooning to initiate we must first decide which two routes to merge. This is the second step in our platooning algorithm and can be formulated in several ways. The first technique we will cover is the nearest customer method. Based around the nearest neighbour initial method, pairs of initial customers are created based on their nearest neighbour. Once the list has been completed, they are then ranked according to their distance apart from one another. The smallest distance between the pair of initial customers is ranked highest with the largest distance ranked lowest. Once this list has been created and stored the platooning algorithm starts with the highest ranked pairing and begins identifying the splitting point. In our basic platooning method this is at one of the customer pair locations.

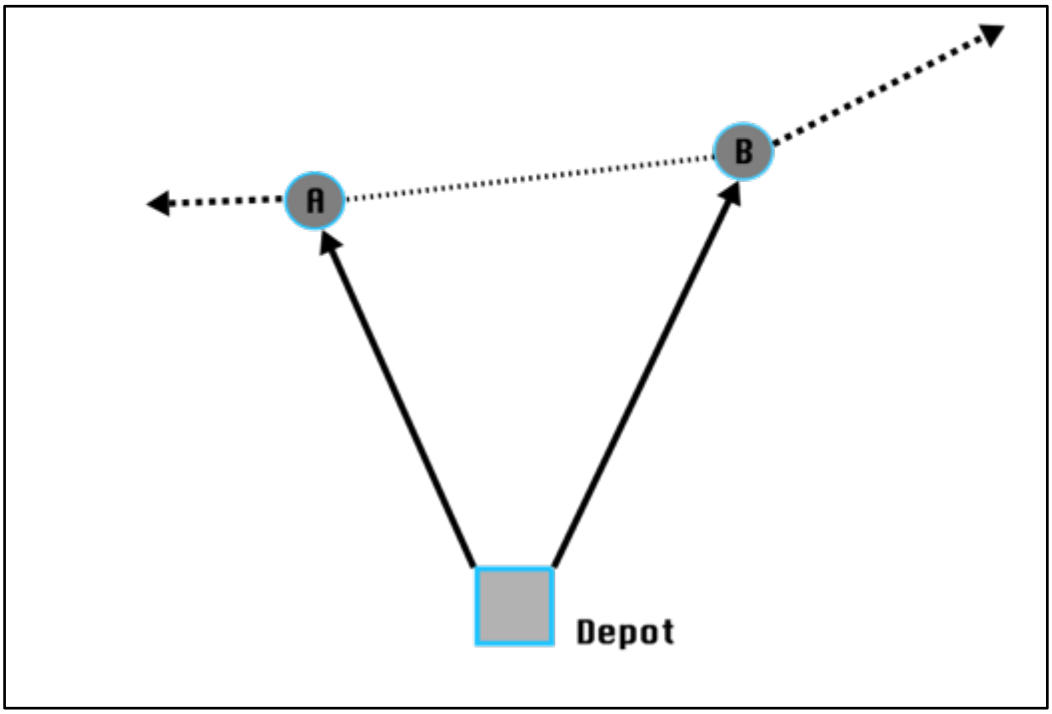


Figure 3.4.16 Initial Platooning with triangle creation

The example shown in the following section is taken from the Christofides_21 dataset where the Basic Platooning algorithm is applied to the VNS algorithm. Figure 3,4,17 shows the optimised routes from the VNS solution including the reversed routes, this solution is also the optimal solution in terms of distance found within literature.

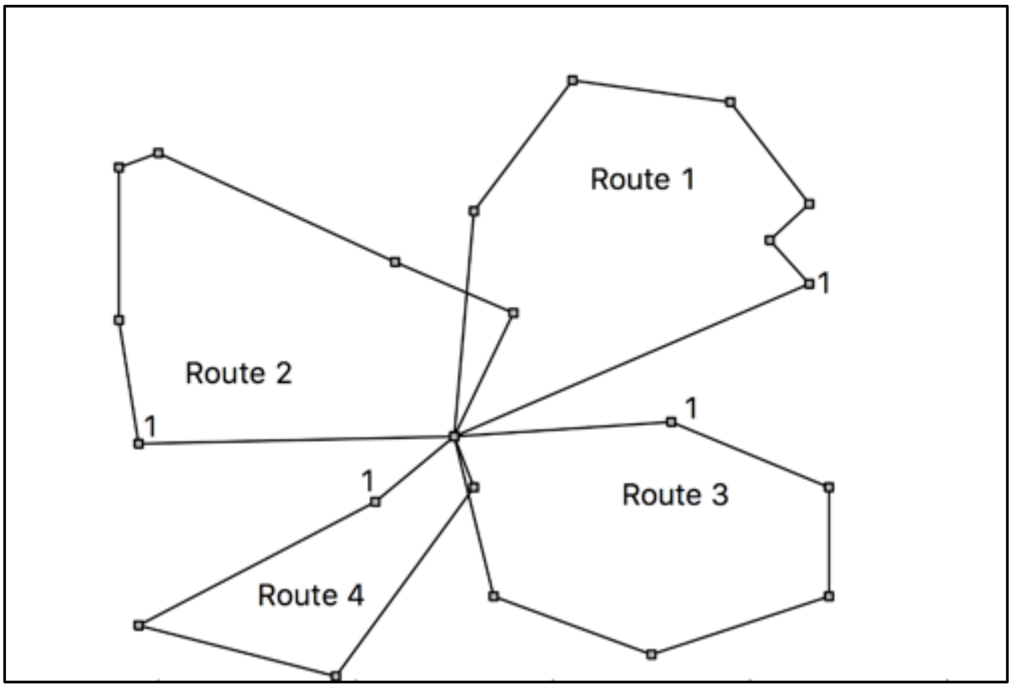


Figure 3.4.17. Optimal solution of the Christofides dataset with 21 customers.

In this instance only the first customers of each route are being altered and considered for platooning. The initial customers of each of the routes can be seen in Figure 3.4-14 and are denoted by “1” of the relevant routes. The distances, average MPG per arc, fuel consumption and the CO2 are provided in table 3.4-13:

Table 3.4-13. Emissions data for the optimal distance solution

Route Number	Initial Arcs (customer number)	Distance (miles)	Average Miles per Gallon	Fuel (Gallons)	Co2 (kg)
Route 1	0-9	27.7	23	1.204	12.247088
Route 2	0-13	16	24	0.667	6.78126552
Route 3	0-12	11.2	24	0.467	4.74686552
Route 4	0-16	9.8	24	0.408	4.15353276
Total/Average MPG		64.7	23.75	2.746	27.9287518

The first case that is assumed, is that the platoons must visit a customer location, i.e. The vehicle on route 1 must visit customer location 1 from route 3. In this instance the vehicles are allowed to visit other customer locations however they are still fixed to the customer location coordinates, and so this method will be referred to as the Fixed Customer Platooning approach. In table 3.4-13 only the initial arcs are shown for each route, with the customer number of the depot and first customer showing. This fixed positioning of the split points has real world applicability as delivery vehicles can platoon up to the point of delivery. The customer at which the vehicles split was chosen as the nearest customer to the depot of the two routes that can be feasibly connected. Figure 3.4.18. Shows the new routes being created. Vehicle 1 from Route 1 is in platoon with Vehicle 3 from Route 3, these vehicles

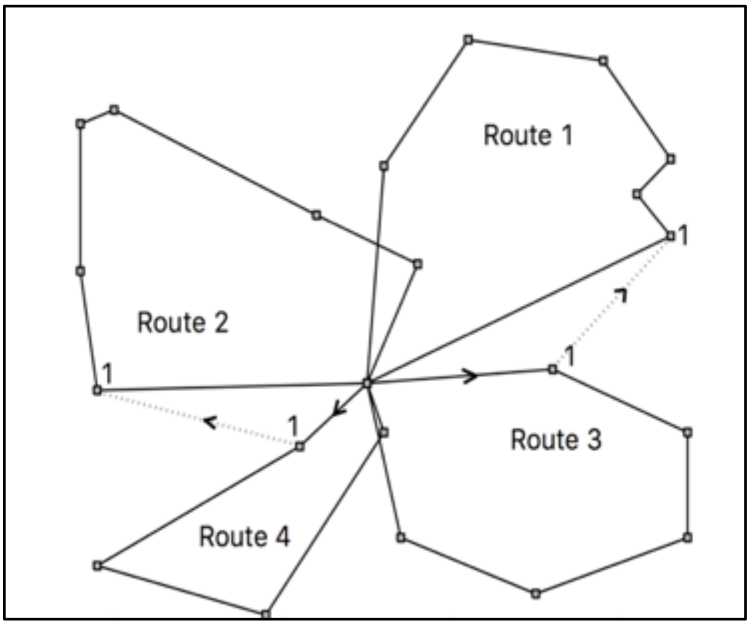


Figure 3.4.18. Fixed customer Platooning result

split at the first customer from Route 3 and continue with their customer deliveries. Vehicle 2 from Route 2 platoons with Vehicle 4 from Route 4 until they reach the first customer for vehicle 4. The new distance of each route is calculated, as is the new MPG. The MPG now must take into consideration the fuel saving benefits vehicles gain via platooning. In this study, as mentioned previously the benefit for a lead vehicle (front of the platoon) is 5% and the tow vehicle (the vehicle following the lead vehicle) is 20%. These values do vary according to speed, however at the average speed of 50mph these values provide accurate representation of the real world. The result from the platooning can be seen in Table 3.4-14.

Table 3.4-14. Emissions data for the fixed customer platooning

Platooning	Route Number	Initial Arcs (customer number)	Distance (miles)	Average Miles per Gallon	Fuel (Gallons)	Co2 (kg)
(towed)	Route 1	0-12-9	31.2	24.65	1.266	12.87490467
(towed)	Route 2	0-16-13	24.2	25.94	0.933	9.489683886
(lead)	Route 3	0-12	11.2	25.2	0.444	**4.520888889**
(lead)	Route 4	0-16	9.8	25.2	0.389	**3.955777778**
	Total/Average MPG		76.4	25.2475	3.026	30.78090108

When comparing the information from Table 3.4-13 and Table 3.4-14, the overall distance for all of the routes to reach their respective first customers increases by 18%. However, the average MPG only slightly increase each route. This is a result of the platooning that occurs on the first leg of each vehicles routes. Vehicles 3 and 4 do not vary their routes but gain an average of 1.2 MPG resulting in a 5% fuel saving, this is because of the platooning where they received a 5% benefit from decreased drag by towing a vehicle. Vehicles 1 and 2 increase their arc distance by 12.6% and 51% respectively but increase their average MPG by 7% and 8% respectively. The massive increase in distance for vehicle 2 in route 2 out ways the gains from the platooning tow unfortunately and as a result emits 40% more CO2 than Route 2 in the shortest path solution. With first customers that are closer together or lie on the same tangent, vehicles deviate less from their original arc. With customers, closer together the effect of platooning is increased. In this example vehicle 1 increases its arc distance by 12.6% however the overall CO2 output is just 5%. In this example, the number of customers is not sufficient to make Fixed Customer Platooning viable, it is hoped that with problems featuring customers in denser locations the benefits will be increased.

3.5 Results and Analysis

Using the basic platooning method, the results achieved are displayed in Table 3.5-1.

Table 3.5-1 Basic Platooning results

Name	BKS	VNS Route Length	Platooning Route Length	VNS Emissions	Platooning Emissions	Percentage Difference of Emissions
1_50	524.61	527.029	595.555	217.274	226.823	4%
2_75	835.26	845.294	936.263	340.916	353.035	4%
3_100	826.14	839.488	971.118	343.567	367.94	7%
4_150	1028.42	1061.91	1178.1	427.178	445.794	4%
5_199	1291.29	1344.16	1402.73	526.467	532.208	1%
11_120	1042.11	1050.4	1167.91	404.484	438.262	8%
12_100	819.56	821.52	861.293	316.109	323.778	2%

Table 3.5-1 shows the basic platoon model results when forcing the Platooning option for multiple pairs of routes. The forced platooning method proved to be detrimental and several routes were merged which caused large increases in route length resulting in increasing emissions. It is suggested that the Platooning options should be only used if they provide a benefit to the specific pair of routes. Potential extensions to such a problem include relaxing the strict platooning option and also relaxing the fixed splitting point on the customers. For the instances tested basic platooning is not recommended, further testing with different datasets is advised.

3.6 Summary

Through this chapter we have developed a model from the CVRP with basic heuristic methods and finished with our basic Platooning model. Of the initial methods tested we have shown that the Clarke and Wright method is superior for instances less than 199 in size due to the better solutions with acceptable computational times. A mention should be given to the improved sweep method and the introduction of capacity changes. When introducing different capacity constraints at the start of the algorithm and then relaxing them later, improvements can be achieved in the final solution. The MPG calculation that is implemented allows our algorithm to check each arc and improve the fuel consumption upon its next iteration. MPG calculations provide a real insight into the emissions created and should be used in the majority of VRP's. Our Basic Platooning model has shown success on some routes although the majority of routes within the instances tested showed an increase in fuel consumption due to the overall increase in distance travelled. While this may be considered a failure, the instances are all calculated with Euclidean distances. In real world scenarios, vehicles traverse across the same major routes as shown in the example at the start of this Chapter. Platooning can provide real benefits when used in real life circumstances. In order to improve on the platooning solution, the vehicles must only travel the extra distance if this is to be negated by the reduction in drag force they experience when leading or in tow of the Platoon. The next chapter looks at improving this splitting point in the hope of providing improved results and further reductions in emissions.

Chapter 4

Advanced Platooning Modelling

Although in certain instances the basic platoon model can generate benefits in terms of CO_2 emissions there is scope for improvement. This Chapter extends the model presented at the end of Chapter 3 with several additional variants. Classical vehicle routing is limited by the customer location, in terms of datasets you are fixed to those coordinates of the customers. In the real world the road network multiple route options are available and often the majority of the same road is traversed to reach different customers. We begin by introducing more complex algorithms based around the splitting point. By creating a new dummy location to act as a splitting point for the platoon more efficiency can be obtained within the optimisation. The addition of this splitting point bares much resemblance to the real world whereby road features such as junctions, roundabouts and service areas can be used as splitting points. Using the techniques discussed within this chapter future researchers can use real locations, and splitting points can be optimised for real perspective logistic companies.

4.1 Improvement from Basic Platooning Model

In the following sections we highlight potential areas where the basic Platooning Algorithm discussed in Chapter 3 can be improved upon. We begin with Reversing of Routes optimising the result before the Platooning Model is applied. This improvement implicates our platooning model by having to provide better solutions. We then introduce new methods for identifying the critical splitting point.

4.1.1 Implications of Reversing Routes

To see the full potential of the advanced method we first implement a reversing routes post optimiser. This further reduces emissions from our VNS solution further. To properly analyse the effect of platooning the we aim to have efficient routes to begin with. The majority of research on the VRP aims at reducing the overall distance. Reversing routes although may not have any impact on the overall distance, still can have an influence on emissions, it is for this reason it is often overlooked. The reader is now referred to Figure 2.1.1, the simple demonstration shows how short arcs with full loads are preferred over short arcs with light loads; due to the reduction in MPG when carrying a lighter load on the longer arcs. By implementing the CO_2 calculation discussed in Chapter 3 Section 4.3 we can evaluate how the MPG changes for each arc of each respective route. Once the emissions solution from the CO_2 calculation is the reversing of each route is attempted and a new CO_2 value for the route is calculated if a better emissions result is found the reversed route is saved. This method similar to Lin's 2-Opt takes the whole route and reverses it, i.e Route *0-1-2-3-4-0* will become Route *0-4-3-2-1-0* where *0* denotes a depot and the numbers refer to individual customers. The results are generated using our VNS solution for the Christofides et al dataset with 21 customers are presented in Table 4.1-1. The table highlights the solution before and after reversing the routes. It can be seen that routes 1 and 4 have been reversed and as such have saved 1.878 kg of CO_2. With routes 2 and 3 no savings were achieved and so the routes we not reversed. The savings achieved on this dataset equates to a 1.2% fuel saving. When implemented on larger scale problems the resulting emission savings are significant. This post optimiser although incredibly simple can provide sizeable benefits when it comes to emissions. With growing CO_2 concerns it is vital that current models' factor in an MPG calculation to provide accurate CO_2 model.

Table 4.1-1 Effectiveness of the reverse routes post-optimiser

ORIGINAL BEST ROUTE	BEST WITH REVERSE ROUTE
Route 1 -> 0-6-1-2-5-7-9-0- Total Distance : 112.17 Gallons Used in Route 1 - 4.5795 CO2 - 46.5827	Route 1 -> 0-9-7-5-2-1-6-0- Total Distance : 112.17 Gallons Used in Route 1 - 4.50395 CO2 - 45.8142
Route 2 -> 0-13-11-4-3-8-10-0- Total Distance : 102.581 Gallons Used in Route 2 - 4.0553 CO2 - 41.2505	Route 2 -> 0-13-11-4-3-8-10-0- Total Distance : 102.581 Gallons Used in route 1 - 4.0553 CO2 - 41.2505
Route 3 -> 0-12-15-18-20-17-0- Total Distance : 83.668 Gallons Used in Route 3 - 3.3155 CO2 - 33.7253	Route 3 -> 0-12-15-18-20-17-0- Total Distance : 83.668 Gallons Used in Route 2 - 3.3155 CO2 - 33.7253
Route 4 -> 0-14-21-19-16-0- Total Distance : 76.861 Gallons Used in Route 4 - 3.09674 CO2 - 31.5001	Route 4 -> 0-16-19-21-14-0- Total Distance : 76.861 Gallons Used in Route 3 - 2.98776 CO2 - 30.3915
TOTAL DISTANCE : 375.28 TOTAL DEMAND : 22500 SPACE AVAILABLE : 1500 TIGHTNESS : 93.33% TOTAL CO2 PRODUCED : 153.059kg	TOTAL DISTANCE : 375.28 TOTAL DEMAND : 22500 SPACE AVAILABLE : 1500 TIGHTNESS : 93.33% TOTAL CO2 PRODUCED : 151.181kg

Throughout this thesis we have used mainly conventional VRP techniques to improve the efficiency of the routes, we now employ our advanced platooning model to try and further improve upon these routes.

4.1.2 Improved Platoon Route Pairing

Following on from the initial route paring discussed in Chapter 3 section 3.4, we now introduce an improved pairing technique. This method calculates the angle between two initial customers of two different routes and the depot. Figure 4.1.1 demonstrates the importance of pairing these initial customers so that the smallest angle is preferred.

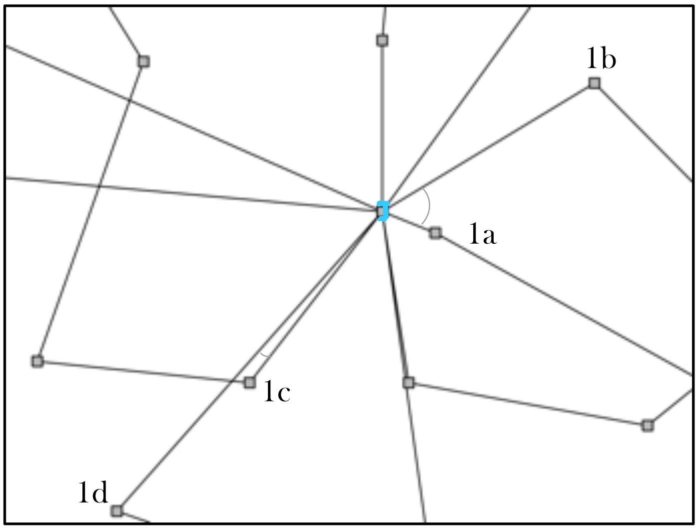


Figure 4.1.1 Zoomed in Solution to a VRP

With a smaller angle between customers a smaller deviation is needed from the original routes resulting in larger savings. In Figure 4.1.1 first customers for routes a and b denoted as 1a and 1b respectively, have a large angle between them when starting from the depot shown in blue. This therefore is not an efficient pairing for a platoon, due to the extra distance that is needed to travel arising from the deviation to the splitting point. First customers for routes c and d denoted as 1c and 1 d respectively, have a very tight angle from the depot. This is favoured when pairing as a small deviation is needed and the platooning benefit is maximised. The pairing algorithm is similar to the sweep technique covered in Chapter 3 for creating the initial routes, however in our case we only consider the first customers of a route (or last customers if the route is reversed). Platoon parings are created as a sweep occurs from a set starting point with the depot as origin, this starting point is initially taken to be the first customer of the first route. Once the sweep has been completed the list of angles between the first customers of the routes and the depot are ordered so that the smallest angles are ranked highest. When creating splitting points, the initial customers from the two routes that are ranked highest are calculated first as these have the highest chance of producing beneficial platoons. Using this improved platoon route pairing we can achieve the most preferable platoons quickly and efficiently that creates a good starting point for our platooning algorithm.

4.1.3 Lateral Shift Split Point

The point at which vehicles split is critical, by allowing the algorithm to alter the splitting point we can reduce the overall extra distance travelled due to the platooning. We begin by allowing the splitting point to be able to move freely along an imaginary arc between the first two customers of the two routes we are platooning.

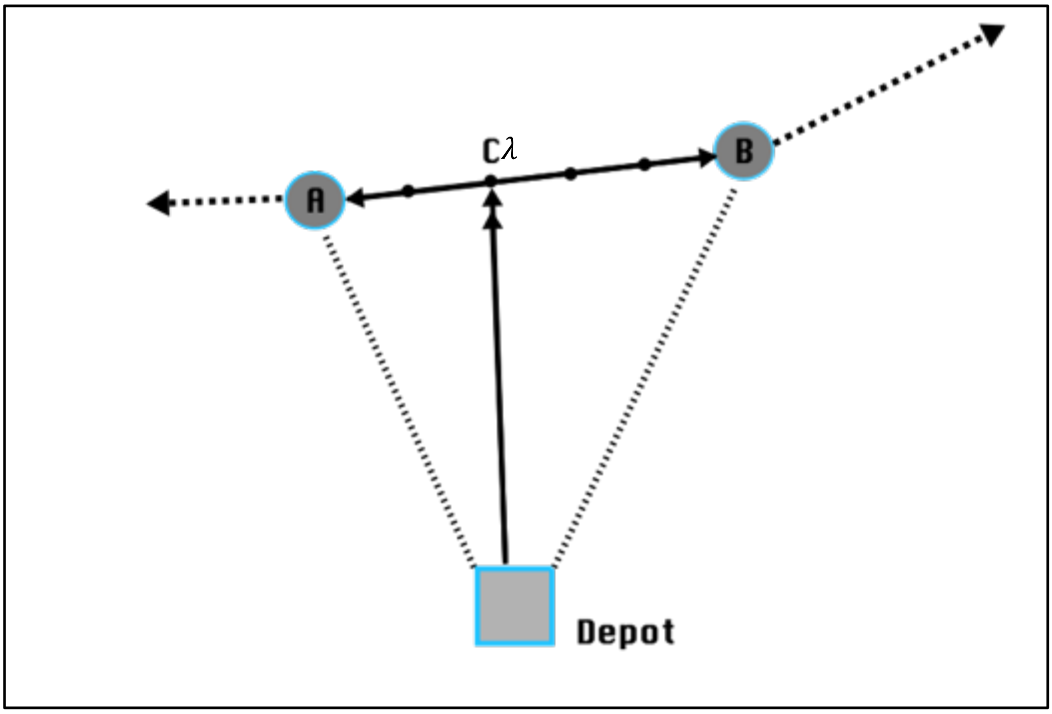


Figure 4.1.2 Moving the splitting point example

Figure 4.1.2 shows how the platoon travels up to a split point $C\lambda$ situated between the intersect of the first customer *AB.* The point at which they split can be presented using the following formula:

$$C\lambda = \lambda A + (1 - \lambda)B \qquad \lambda \in (0,1)$$

When $\lambda = 1$ then the platoon will split at customer *A* and similarly when $\lambda = 0$ the platoon will split at customer *B.* By iteratively increasing the value of λ by small values (<0.1) we can test many split points along the line *AB.* Once multiple values of λ have been tested the best value in terms of emissions is chosen. The following example shown in Figure 4.1.3 was simplified to allow the split point to be created at the midpoint of the first two customers on the platooning routes. The new routes are created and the paths which the vehicles now take when the platooning can be seen with the dotted line.

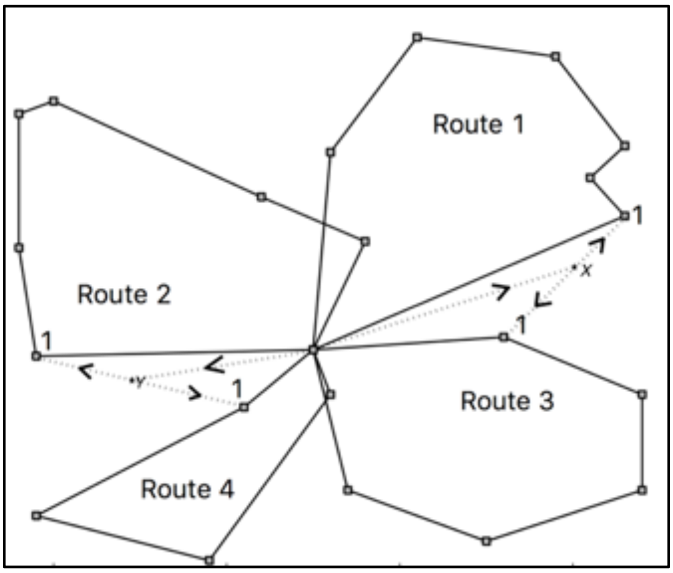


Figure 4.1.3 Split points at the midpoint of first customers for routes 1,2,3 and 4.

Letters X and Y identify where the split points occur. These were calculated by taking the midpoint of the first two customers of the platoon route candidates in this instance i.e When $\lambda = 0.5$. Table 4.1.2 shows the results platooning to the split point set at the midpoint and the routes without platooning.

Table 4.1-2 Emissions and Fuel Usage using the Lateral Shift Split Point

Platooning	Route Number	Arc (customer number)	Distance (miles)	Average Miles per Gallon	Fuel (Gallons)	Co2 (kg)
(towed)	Route 1	0-x-9	28.630	25.970	1.102	**11.214**
(towed)	Route 2	0-y-13	18.390	26.190	0.702	7.143
(lead)	Route 3	0-x-12	28.630	24.776	1.156	11.754
(lead)	Route 4	0-y-16	18.390	24.729	0.744	7.565
	Totals/Average MPG		94.040	25.416	3.704	37.675
Non-Platooning	**Route Number**	**Arc (customer number)**	**Distance (miles)**	**Average Miles per Gallon**	**Fuel (Gallons)**	**Co2 (kg)**
	Route 1	0-9	27.700	23.000	1.204	12.247
	Route 2	0-13	16.000	24.000	0.667	6.781
	Route 3	0-12	11.200	24.000	0.467	4.747
	Route 4	0-16	9.800	24.000	0.408	4.154
	Totals/Average MPG		64.700	23.750	2.746	27.929

The overall distance of the first arcs in this case increase by 45% from the original, this badly effects the CO2 where the platooning benefit cancel out the effect. Vehicle 1 benefits from a reduction of CO2 of 8.5%, this is due to the increased platooning time. Unfortunately, vehicle 3 which formed the lead part of the same platoon experiences a large increase in emissions, largely down to the 250% increase in arc length. From Figure 4.1.3 the midpoint split point means that vehicle 3 must travel far beyond its initial customer location resulting in excess distance travelled. As this is the start of the journey extra distance has the greatest effect on CO_2 as the MPG is lowest when the vehicle is loaded to its maximum. The average MPG of each route does increase, although as mentioned prior, the increase in route length outweighs the benefits of this MPG increase. This approach does not work well for scattered datasets and with more clustered dataset the results would improve as the angle between the first customers would be smaller resulting in less extra distance travelled due to the platoon. Further investigation into the creation of the routes and how they can be improved can be found in section 4.1.2. By allowing the splitting point to move along the intersect of the first customers of two routes we have reduced the excess distance travelled when platooning. In order to achieve better results, we now investigate this splitting point further by allowing the split point to move freely.

4.1.4 Enhanced Split Point

We can also take the split point one step further and try and identify the optimum splitting point. This would provide key insight into where platoons can split in real life instances. With services and junctions providing the available candidate points for splitting. The decision as to where the platoon splits is essential, splitting at the incorrect point can incur an increase in overall fuel use. Extending the previous method further we begin to move the splitting point towards the depot. The reader is directed to Figure 4.1.4. Once we have the optimum λ point along AB the optimum splitting point will be along the line of $C\lambda$*-Depot*. Using the same technique as before we iteratively test the points in small distances (In our example case of the Christofides 21 the iterations were 0.1 of unit length). The formulation of Figure 4.1.4 can be written in the following equation:

$$D\alpha = \alpha C + (1-\alpha)Depot \qquad\qquad \alpha \in (0,1)$$

When $\alpha = 1$ the platoon will split at end on the line *AB* at point $C\lambda$, when $\alpha = 0$ the platoon will not form, and the split will be from the Depot. This allows the algorithm the opportunity not to force the platoon and only accept an improvement. Once multiple values of α have been tested the best value in terms of emissions is chosen and the optimum splitting point $D\alpha$ is chosen. During testing we found 3000 values α provided good resolution with no significant increase in computational time with small circumstances, with larger datasets the resolution may need to be reduced to maintain computational time. It should be noted that the optimum point will lie within a minima, i.e either side of the optimum splitting point if α is altered by $\pm 2\delta$ the splitting point will have worst emissions values than the values at $\pm\delta$. Using this solution space can be reduced and the iterations using λ and α can stop when the solution value increases, saving unnecessary calculations and computational time. For the sake of these examples this is not explored however it is a recommended avenue for future research.

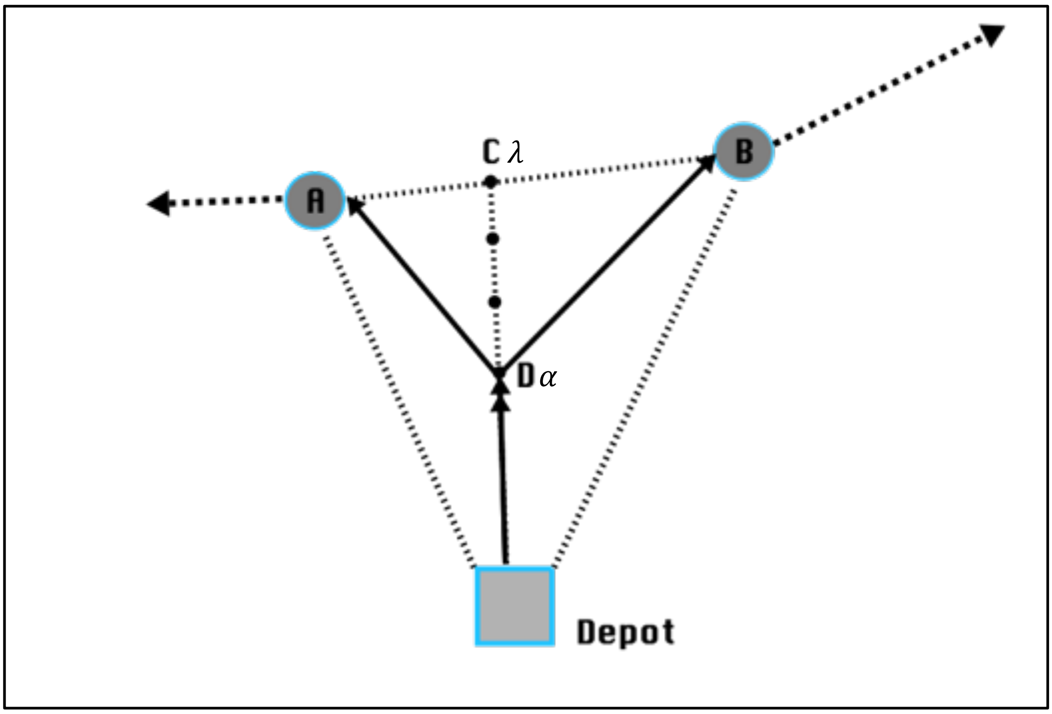


Figure 4.1.4 Enhanced split point example

The example that will be discussed here is the Depot-Midpoint Split where $\lambda = 0.5$ and $\alpha = 0.5$, this method creates another split point at the midpoint from the depot and the midpoint created in the Lateral Shift Point in section 4.1.3, (between the initial customers). Figure 4.1.5 shows where these split points occur and are identified by X and Y. By creating the split points closer to the depot, the vehicles have less deviation from their original arcs resulting in a shorter distance than the Lateral Shift Point approach.

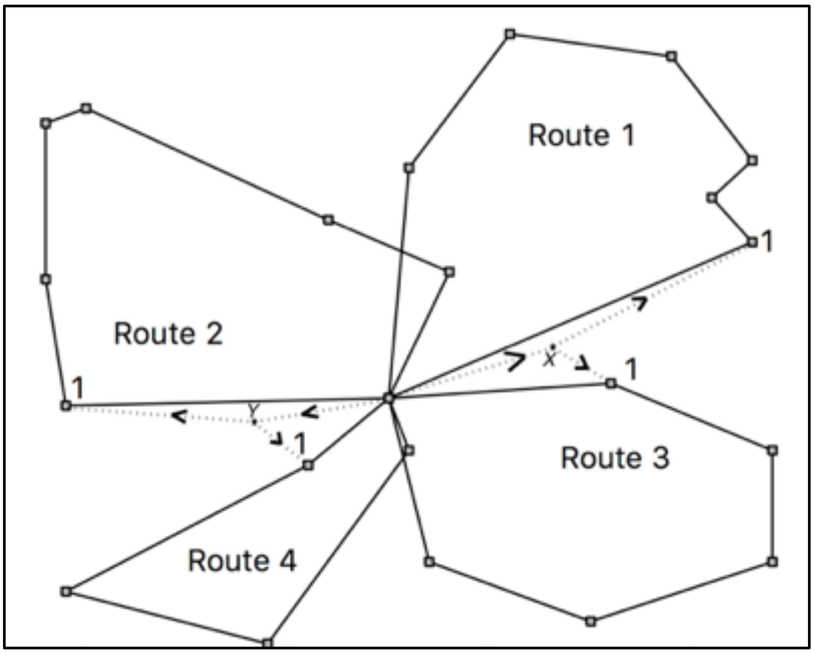


Figure 4.1.5. Depot-Midpoint split point

Table 4.1-3 provides the results from this example with the enhanced split point. In this example for simplicity it should be noted that the mid-point where $\lambda = 0.5$ and $\alpha = 0.5$ is used, potential further benefits can be achieved when allowing further values of λ and α.

Table 4.1-3 Emissions and Fuel Usage using the Lateral Shift Split Point

Platooning	Route Number	Arc (customer number)	Distance (miles)	Average Miles per Gallon	Fuel (Gallons)	Co2 (kg)
(towed)	Route 1	0-x-9	27.910	24.530	1.138	**11.574**
(towed)	Route 2	0-y-13	16.690	25.610	0.652	**6.629**
(lead)	Route 3	0-x-12	14.550	24.760	0.588	5.977
(lead)	Route 4	0-y-16	12.166	24.550	0.496	5.041
	Totals/Average MPG		71.316	24.863	2.873	29.221
Non-Platooning	**Route Number**	**Arc (customer number)**	**Distance (miles)**	**Average Miles per Gallon**	**Fuel (Gallons)**	**Co2 (kg)**
	Route 1	0-9	27.700	23.000	1.204	12.247
	Route 2	0-13	16.000	24.000	0.667	6.781
	Route 3	0-12	11.200	24.000	0.467	4.747
	Route 4	0-16	9.800	24.000	0.408	4.154
	Totals/Average MPG		64.700	23.750	2.746	27.929

The overall distance for the initial arcs from this approach are approximately 10% longer than the optimal shortest route solution, however the resulting CO2 is only increased by 4.6%. Vehicles 1 and 2 both see a reduction in fuel consumption and CO2 emissions. This is because the routes only increase by a relatively small amount and the vehicles both receive the towing benefits from platooning. With further optimisation of the split point with multiple values of λ and α improvements for all vehicles can be achieved, this can have a large effect on the overall CO_2 as demonstrated in the last two approaches. Further modelling with more datasets with differing characteristics is suggested as future research, with the hope of identifying which variation of dataset i.e cluster/scatter/radial responds best to platooning.

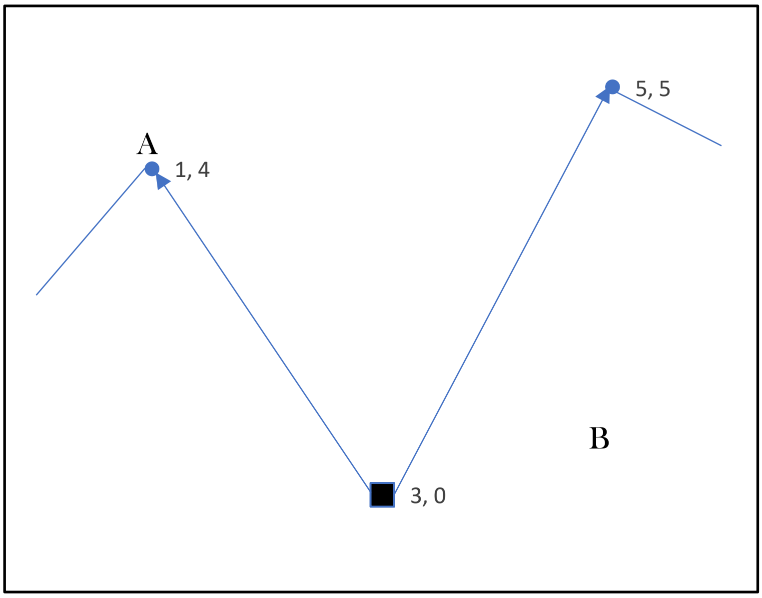


Figure 4.1.6. Graphical representation of the start of two initial routes (not to scale)

In order to provide the reader with a visual representation of the effects moving the splitting point (providing multiple values of λ and α) we investigate bilinear interpolation to locate the minima of platooning examples with varying angles between the first customers and the depots. Bilinear interpolation is an extension of linear interpolation and is used here to interpolate two functions of λ and α.

Figure 4.1.6 shows another example case that will be used throughout the remainder of this section as we believe it best represents the effects of the enhanced split point. The Depot (D) is positioned at the coordinates (3,0), customers A and B are the first customers for vehicle 1 and vehicle 2 respectively.

Using the distance formula derived from the Pythagorean Theorem one is able to find the distance between two points (x_1, y_1) and (x_2, y_2), this formula is shown the equation below.

$$Distance\ between\ two\ points = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

Vehicle 1 departs the depot and travels to its first customer, A, a total distance of $\sqrt{20}$, Vehicle 2 departs the depot and travels to its first customer, B, a total distance of $\sqrt{29}$. The combined distance equates to ≈ 9.857. Take this distance to be L_{Before}.

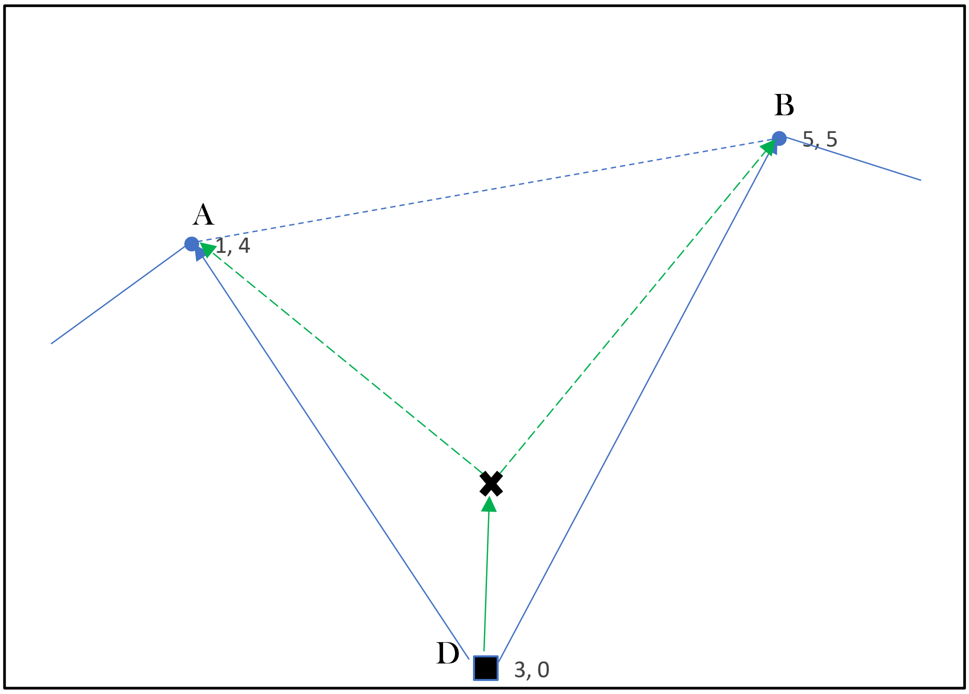


Figure 4.1.7. Example Platoon point inserted. (not to scale)

The point at which the vehicles split from the platoon is shown in Figure 4.1.7 by X. From D to the point X both vehicles gain their respective platooning benefit, and after continuing onto their respective customers. The position of this point is very important to the benefit of the Platoon procedure. Considering both vehicles traverse the same platooning arc together one can therefore use the average benefit of both vehicles for each route/vehicle, i.e each route will equate to

$$\frac{Lead(0.96) + Tow\ Benefit(0.79)}{2} + XA\ or\ XB$$

DXA and DXB can be thought of two individual triangles. Therefore, the problem can be defined as: is the added distance of traversing along $2DX(0.875) + XA + XB$ more economical than travelling across the hypotenuse $DA + DB$. In order to maximise the efficiency of the optimisation boundaries/constraints need to be in place to reduce the size of the search space. Examples of various scenarios were created in order to determine where these boundaries are and when they are influential.

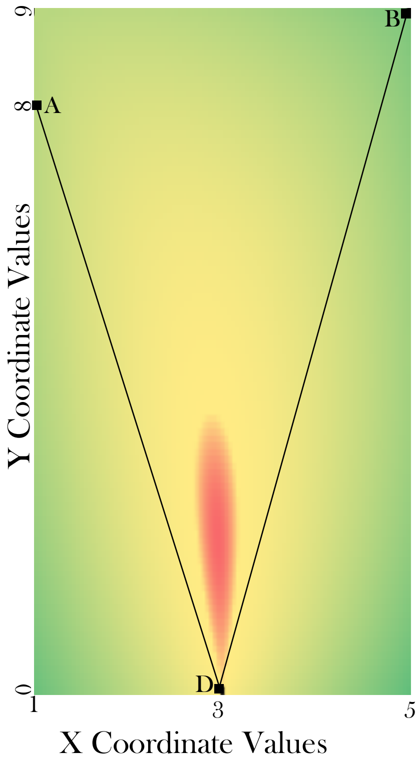


Figure 4.1.8.Bilinear Interpolation identifying benefit points (shown in red) to be considered when splitting from the Platoon

Figure 4.1.8 displays a bilinear interpolation for the potential splitting points of the platoon. A and B represent the first customers of two routes, the depot is denoted by D. In this instance the solution space was limited to within the triangle DAB, as it was hypothesised from our previous investigation that outside this region there would significant additional distance traversed, and this would be too costly. The region highlighted in red are points at which the platoon split should be placed, when the platoon splits within this region the fuel consumption of the problem is reduced overall. It must be noted that the benefit is only achieved in a small area of the available search space for this example. If the platoon was split within the yellow or green area no emission benefit from platooning would be achieved. This area is highly effected by the angle of $A\widehat{D}B$.

As mentioned previously the angle at which the first customers of the two routes being formed into the platoon of great importance. Further investigation as to how the angle $A\widehat{D}B$ effects the Bilinear interpolation function is now carried out. We carried out testing with bilinear interpolation for 4 different angle scenarios: $A\widehat{D}B < 15^{\circ}$, $A\widehat{D}B < 35^{\circ}$, $A\widehat{D}B < 60^{\circ}$and $A\widehat{D}B < 70^{\circ}$ with the hope of providing good graphical representation of potential splitting points for different scenarios. Once the angle $A\widehat{D}B$ reaches a certain value platooning is not beneficial. Figure 4.1.9 shows 4 of these results, they provide good results from each of the scenarios and were chosen as they provide good representation of the other angles within each scenario, the full testing included each angle being calculated for every degree from 5° to 65°. Figure 4.1.9 highlights the benefit of the platoon effect when small angles are present. It can be seen that with a smaller angle between the first customers a larger area for the platoon to split is available, this is shown by the large red area in Figure 4.1.9a. Within this red zone the platoon can split with a fuel reduction benefit. Figure 4.1.9b has smaller area available for the platoon split, however there is still with a clear area where the splitting point can occur with emissions benefits. Figure 4.1.9c has a much smaller area where improvement can be found and the benefits for platooning here are insignificant. Figure 4.1.9d has gone beyond the limit angle and as such there is no improvement that platooning can achieve. This angle is the limit at which platooning can be effective above this angle the additional distance required for platooning renders no emission benefits. The decision on where to split is very much dependent on the angle $A\hat{D}B$ as has been shown. While bilinear interpolation is not the optimal way of solving the enhanced splitting point, we believe it provides the reader with a good visual understanding of the benefits.

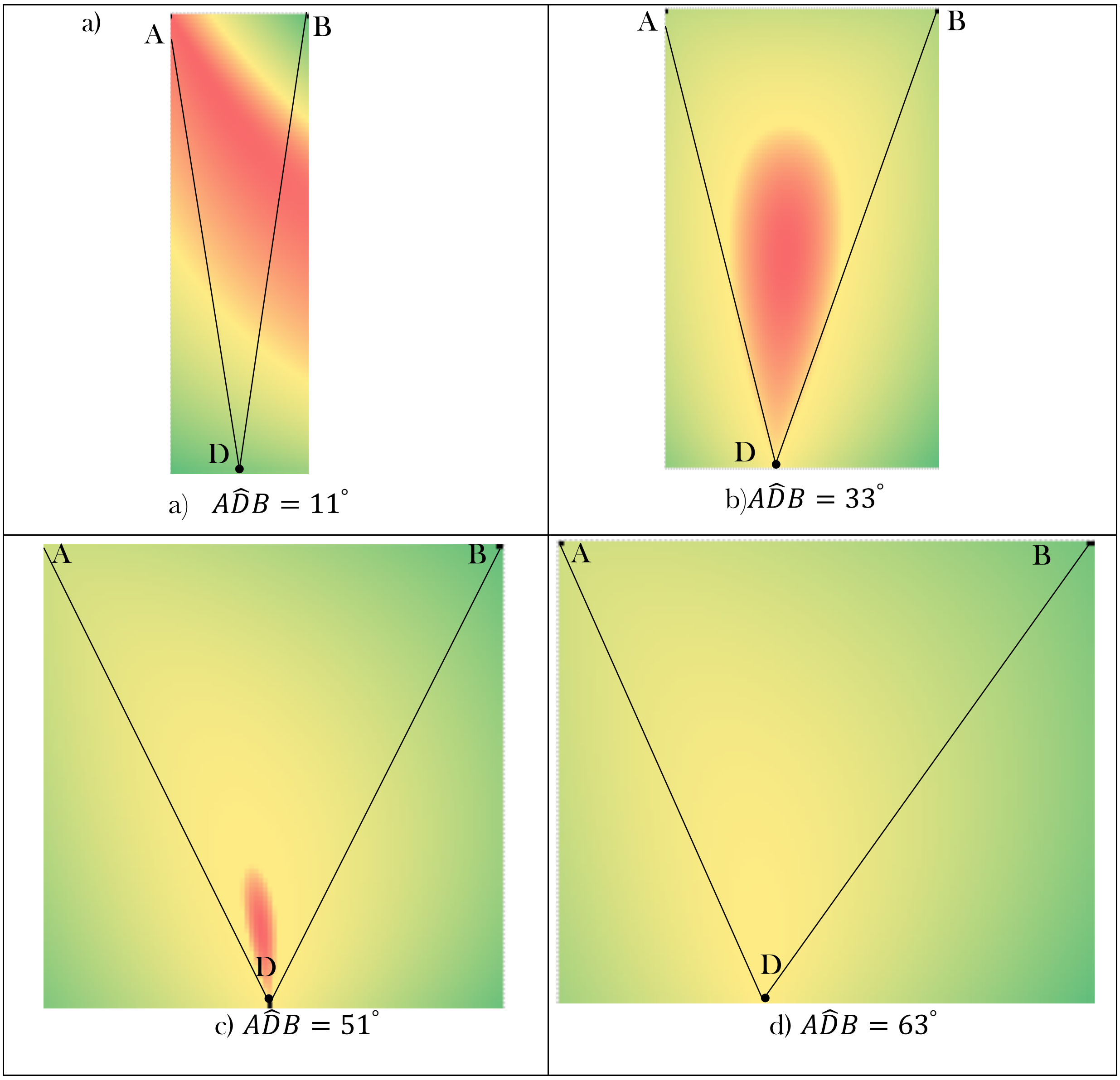


Figure 4.1.9. Four Bilinear Interpolation diagrams for the four different angle scenarios

We now will explore finding the optimal splitting point and will then implement our advanced platooning model with the methods discuss in this section for the Christofides et al. and Golden datasets.

4.2 Optimal Splitting Point

It was mentioned previously that the problem can be broken down into triangles. Following on from this the problem can be seen as identifying the minima, that is the point such that the total distance from each side is a minimum. This problem has been well documented within mathematics and geometry and this point is known as the Fermat point or Torricelli point (Simpson 1750). P. Fermat formulated the problem for Torricelli to solve, since its conception many solutions have been found. Presented in this thesis we demonstrate the Fermat point using Tellier's (1972) graphical method. The process involves 4 steps, firstly constructing equilateral triangles along each side of the main triangle. Then, when constructing these new triangles introduce 3 new vertices on the far vertex of the newly created triangles. Draw a line from each of these new vertices to the vertex of the main triangle opposite. The point of intersection of all 3 lines is the isogonic centre. Figure 4.1.10 demonstrates this construction technique with the main triangle as A, B and C, with new vertices denoted by P, Q and R.

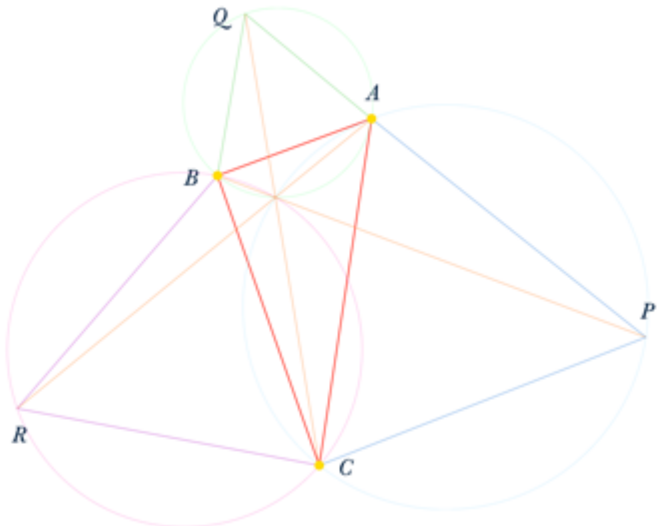


Figure 4.2.10. Identifying the Fermat / Torricelli Point.

The interior angles of the triangle $C\hat{B}A$ and $C\hat{A}B$ are important when it comes to calculating the Fermat point. If any of these angles reaches 120° or more then the Fermat point is found at this vertex. When Platooning we can simulate this very case outlined in figure 4.1.10, the depot can be considered point C with initial customers B and A. With the two vehicles platooning from the depot until the Fermat point. Mentioned previously there is an aerodynamic benefit with platooning, and this provides a benefit to the vehicle's mpg. Fuel usage is also directly related to the distance travelled, therefore theoretically the platooning distance can effectively be considered to be reduced if there was no mpg benefit. To see the effect the Fermat point has when platooning is considered figure 4.1.11 provides the same basis as figure 4.1.10 but with a

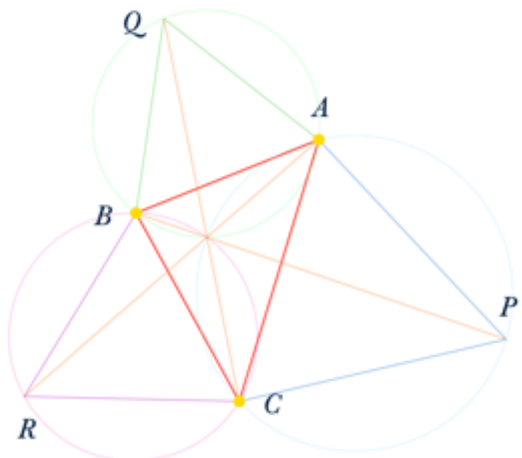


Figure 4.2.11. Platooning and Identifying Fermat Point

shorter route from the depot C and the Fermat point, the intersection of the 3 lines through the vertices. Interestingly the Fermat point does not alter when changing the length of the platoon. Upon further investigation the three circles that intersect Fermat's point and the three lines joining the vertices of ABC with opposite vertices of the equilateral triangles concur at the Fermat point. Changing only 1 point, in this case point C, in the same plane as the line CQ doesn't alter the circle falling on points Q, A and B. This therefore proves that the Fermat point will also be the optimum splitting point and the effect of platooning doesn't affect the Fermat's point calculation. By altering the effective costs per distance, the problem now turns into the Weber problem. Formulated by Simpson & Thomas (1750) and the first direct numerical solution found by Tellier (1972). Whilst a geometrical solution existed Tellier was the first to provide a non-iterative numerical solution. Tellier's method is the recommended solution to be used to identify the optimum splitting point and to be used within the platoon algorithm for best results.

It should be noted that the solution for the objective function is quite shallow in the neighbourhood of the optimum, it is therefore recommended that for best results relating to real life that a combination of Tellier's method and the bilinear interpolation is used to identify multiple possible splitting points all that would benefit the platoon. With potential splitting points already fixed in real life, the optimal solution may not be achievable however if a definite benefit can be achieved in a certain area where a potential splitting point lies then this can be used.

4.3 Results

The results are displayed in a tabular form from the advanced platooning method and are displayed in Table 4.2-1. Figure 4.2.1 shows the graphical result after our advance platooning method was applied to the Christofides 5_199 dataset. The red lines highlight the arcs that are travelled for the tow vehicles after platooning, these are the additional routes they travel after the

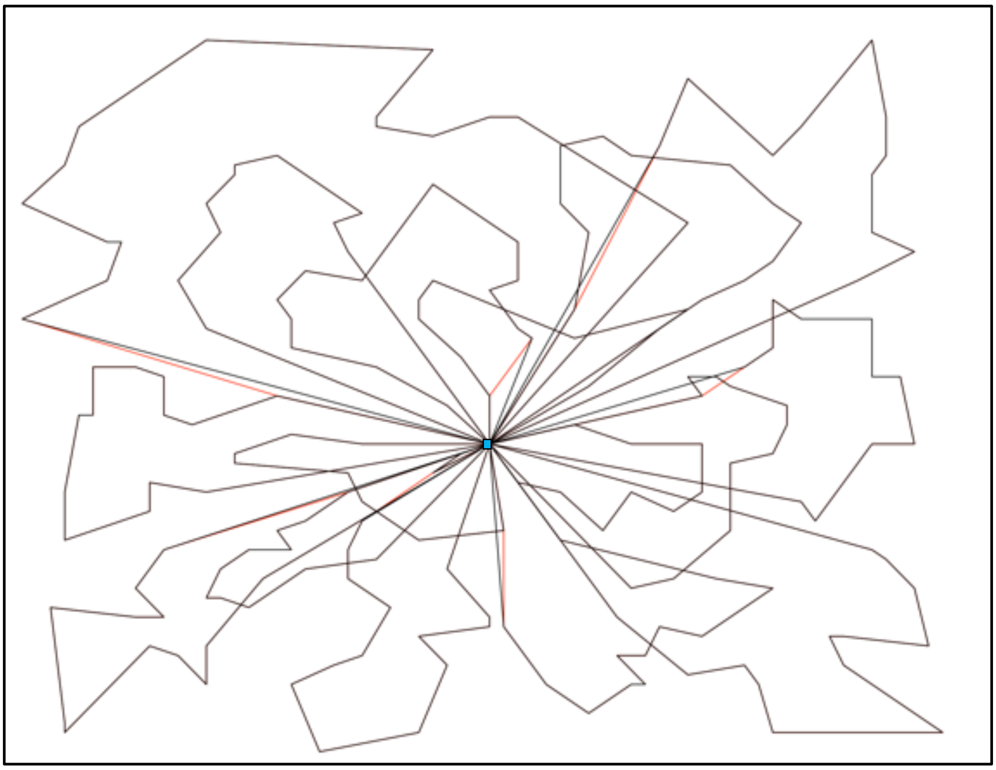


Figure.4.3.1 Advanced Platooning implemented Christofides 5_199

splitting point. The black lines show rest of the planned routes generated from the VNS solution. It can be seen that the platoon only forms on very small angles between the first customers as expected. This drops the overall CO_2 consumption of this example by 1% when compared to our VNS Solution.

Table 4.3-1 Results from Advanced Platooning

Name	BKS	VNS Route Length	Platooning Route Length	VNS Emissions CO_2 kg	Platooning Emissions CO_2 kg	Percentage Difference CO_2kg
1_50	524.61	527.029	575.491	217.274	219.133	0.86%
2_75	835.26	845.294	916.089	340.916	345.618	1.38%
3_100	826.14	839.488	928.293	343.567	351.506	2.31%
4_150	1028.42	1061.91	1132.93	427.178	429.53	0.55%
5_199	1291.29	1344.16	1370.36	526.467	**519.0607**	**-1.41%**
11_120	1042.11	1050.4	1053.29	404.484	**401.391**	**-0.77%**
12_100	819.56	821.52	853.559	316.109	320.894	1.51%
Golden 1_240	5627.54	6704.34	6790.48	2581.67	2596.58	0.58%
Golden 2_320	8447.92	9526.63	9573.62	3668.7	3670.45	0.05%
Golden 3_400	11036.23	12474.4	12516.7	4805.91	**4803.21**	**-0.06%**
Golden 4_480	13624.52	15290.9	15333.2	5903.97	**5896.59**	**-0.13%**
Golden 5_200	6460.98	6988.88	7065.35	2697.93	2722.05	0.89%
Golden 6_280	8412.88	9173.14	9206.65	3545	**3544.14**	**-0.02%**
Golden 7_360	10195.56	11374.3	11416	4387.68	**4384.99**	**-0.06%**
Golden 8_440	11663.55	13467.4	13510.2	5195.65	**5187.06**	**-0.17%**
Li 21_560		18562.8	18605.8	7162.87	**7137.13**	**-0.36%**
Li 22_600		17899.2	18008.5	6898.91	**6857.79**	**-1.01%**
Li 30_1040		39826.8	39986.5	15389.7	**15245.2**	**-1.01%**

Instances for Christofides et al. 5_199, 11_120 and Golden 3_400, 4_480, 6_280, 7_360, 8_440 and Li 21_560, 22_600, 30_1040 resulted in reduced emissions when fixed point platooning was introduced to the first customers. Upon inspection of the route outputs our algorithm forced some platoons that were not beneficial, and this is shown in the results of the other instances where an increase in emissions were seen. Overall, the results show the capabilities of the Platooning method, with significant savings of emissions achieved in the majority of the problems that were modelled.

4.4 Summary

Following on from Chapter 3 where we introduced our basic platooning model this chapter focuses on improving that model and developing a more advanced platooning model incorporating modelling techniques designed to move the splitting point and provide tighter constraints on the platooning options. Reversing the routes produced by the VNS solution does not make any difference to the distance solution, it can however improve the emission solution. By reversing the routes, the vehicles paths are investigated more closely and longer paths with lighter loads are preferred. Including this post optimiser shows good results and improved the VNS emission solution by 1.5% in the Christofides et al. 1_50 instance. Once an improved solution was found our advanced platooning model was implemented. This began by modifying the way in which the platoons were selected and paired when comparing to our basic platooning model. Similar to the sweep method our Improved platoon Route Pairing method sweeps around the initial customers of each route ranking them in order of smallest angle between them. By doing this the vehicles deviate less and gain more of a benefit from the platoon. In order to improve the platooning solution, the splitting point is key, by moving this splitting point we can reduce the unnecessary route distance when platooning of the vehicles. The first improved method is the Lateral Shift Split Point, the split point is moved along the arc created by the two first customers. Here benefits are seen when there is little difference in distance from the depot to the first customer of both platoon routes, within our example the angle is fairly large and as a result we don’t achieve the emission reduction expected. The lateral shifting of the split point reduces the distance travelled and allows vehicles to deviate less. Several routes saw a further reduction in fuel but specific routes where the different distances between depot and initial customers, caused one of the vehicles in the platoon to double back on itself, increasing its journey distance and negating the platooning benefit. In order to stop this from happening the Enhanced Split Point was introduced, here the splitting point can move freely and provides better results for all instances. We provide the reader with a detailed graphic visualisation of the importance of this splitting point using bilinear interpolation and the optimum splitting point found by using the Tellier Method. The results show that the smaller the angle the more options there are for the platoon splitting. While an optimum splitting point may not be feasible in real-life situations/routing a combination of Tellier's method and bilinear interpolation could be used to provide suitable splitting points that would still create emission reduction benefits. Computational times are increased as multiple points are attempted within the algorithm with the best being accepted ultimately optimising the splitting point. In order to reduce this computational time investigation into the angles between the initial customers was needed. It was found that angles larger than 59° no matter the distances between the depot and the first customers are not worth platooning. The results show emission savings in 7 of the 15 tested instances, while still being forced to platoon. With this constraint being relaxed it is hoped all routes will benefit and is advised for future research.

Chapter 5

Electric Powered Vehicles

5.1 Introduction

Green logistics has attracted increased attention from researchers recently due to the growing public environmental awareness as well as the legislations by numerous governments around the world. Road transport is a major factor in climate change and accounts for a large proportion of the total greenhouse emissions, including Carbon Dioxide (CO_2). With traffic and congestion levels growing, greener vehicles (more environmentally friendly) combined with efficient transport routing strategies will be of great importance. Transport organizations have to increase their awareness of the potential impacts their activities and services have both, internally and externally as they grow and develop. For example, the UK government has set their targets high and aim to reach their goal from the Climate Change Act (Climate Change Act 2008) of reducing the UK's GHG emissions by at least 80% by the year 2050 when compared with 1990 levels. This policy requires a drastic reduction in emissions as the road transport industry is one of the main contributors to these negative impacts. We believe this aspect ought not to be ignored where attention should be focused. Climate change is happening as shown by the evidence across several key indicators including the major four as noted below (Progress Report to Parliament Committee on Climate Change 2018).

- Atmospheric CO_2 (Carbon Dioxide) concentrations continue to rise, now exceeding 400 parts per million.

- Global average surface temperature has increased further with 2017 being in the top three warmest years on record. Recent years have exceeded 1°C above pre-industrial levels.
- Artic Sea Ice is still in decline, September sea-ice extent has declined on average 13% each decade since 1979.
- Global sea level has been on the rise since 1990's.

According to the International Energy Agency's figures (International Energy Agency 2017) global emissions are still on the rise though emissions produced by developed countries were in fact reduced by 8% in 2015 when compared to the year 2000. However, developing countries doubled their emissions over that same period. This can be attributed to several factors including a very strong growth in per-capita economic output (+90%) combined with population growth (+23%). The CO_2 intensity of the energy mix also increased (+12%), mainly due to higher coal consumption in larger countries. (International Energy Agency 2017). Among the developed countries, the UK reduced emissions in 2017 by 3% compared to the previous year, with the power sector being most successful in reducing its emissions in electricity production with a 75% reduction in 2018 from 2012. However, while other sectors including buildings and industry also saw a reduction in emissions, transport consumed an increase of 1% in 2017 over the previous year. Since 2014 transport has been the largest emitting sector of the UK economy accounting for a staggering 27% of UK greenhouse gases produced in 2017. Cars, Vans and Heavy Goods Vehicles (HGVs) account for the largest percentage of this transport sector. Policies must be introduced in order to meet the UK government's target of 100% of new car sales to be a ULEV (Ultra Low Emission Vehicles) by the year 2040 (ULEV 2015). Alternative fuel powered vehicles can reduce direct transport emissions drastically, and when combined with greener electricity generation could provide an answer to the UK's growing transport emission crisis. However, it is worth noting that their high battery cost and limited range may constrain their effectiveness.

The purpose of this chapter is to highlight the role of green technologies, in particular alternative fuel powered vehicles and provide an insight into the ways in which they can help reduce carbon emissions. We aim to study various options and features related to the green technology (alternative fuel powered vehicles) in terms of emissions in transport logistics and stimulate interest around this research area.

In the following sections, we begin by reviewing some of the key research literature and introduce Alternative Fuel Powered Vehicles (AFVs) providing information on the current UK market, we then go into detail about their various types; including layout, design and features. We provide comprehensive battery specification information; how various power auxiliaries effect the energy consumption, the charging implications for the batteries and the costs involved. We also highlight specific features of the AFV's such as regenerative braking and CO_2 emissions. Multiple avenues are explored when it comes to AFV emissions followed by our models. The modelling section brings together the aspects highlighted in this chapter and provides a theoretical battery model that can be used to assist researchers in future research. Our summary then concludes this chapter.

5.2 Electric Powered vehicles market

Among alternative powered vehicles, the Ultra-low Emission Vehicles (ULEV's) such as Battery Electric Vehicles (BEV's), Plug-in Hybrid Electric Vehicles (PHEV's) and Extended Range Electric Vehicles (EREV's) are becoming increasingly important to cut down greenhouse gas (GHG) emissions and air pollution in the transport sector. The ULEV uptake in the UK is prominent, recent advancement in battery technology means that these electric vehicles are now becoming increasingly viable for general use. Alternative fuel powered vehicles have increased rapidly in popularity in recent years within the UK. Let alone Electric vehicle sales, which have increased from 3,500 in 2013 to more than 150,000 by May 2018 (Electric car market statistics

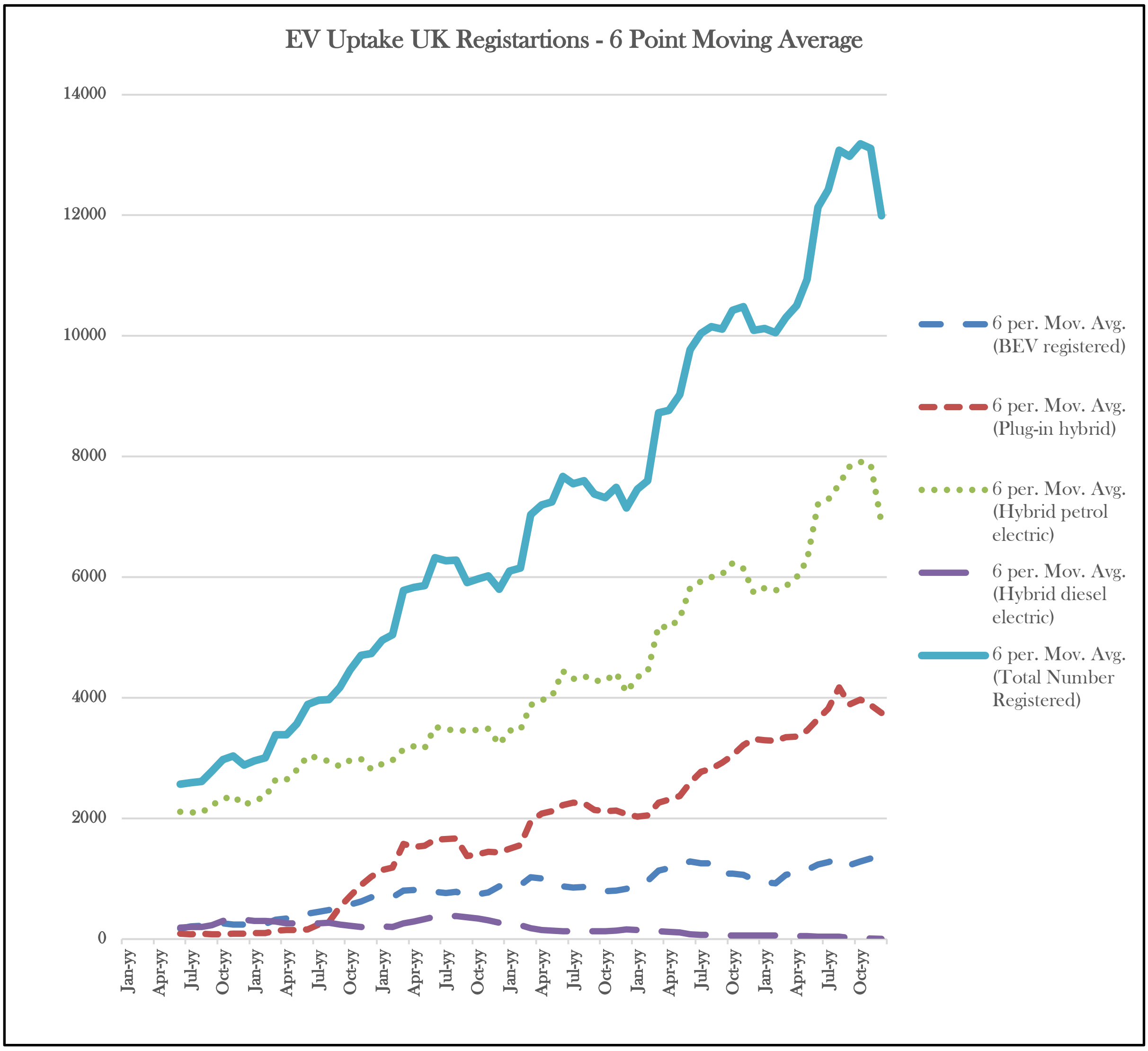


Figure 5.2.1 EV Uptake in the UK over the last 5 years (Data acquired from the Society of Motor Manufacturers and Traders)

2018). Figure 5.2.1 shows the recent Electric Vehicle uptake in the UK on a 6-point rolling average. This particular rolling average is important as it removes the peaks created by the new vehicle registrations that happen in March and September, and the troughs before these months as people wait for the new vehicle registration and dealers purchase a large number of newly registered vehicles in bulk. These peaks and troughs due to the new vehicle registrations are well-known within the motor trade industry. The increase in popularity is evident in the large increase in sales of EV's, the most popular type of EV currently available is the EREV Hybrid Petrol Vehicle, with monthly sales almost doubling in the last 2 years. Plug in hybrids also prove to be popular amongst the UK market with BEV's trailing. The last quarter of 2018 saw zero

Hybrid diesel vehicles registrations, this could be due to a number of factors including the increase in diesel tax, more stringent emission tests and the lack of Hybrid diesel electric vehicles being manufactured. The EV market now has 8% share of the UK New Vehicle market, an increase of 7% from July 2013.

5.3 Electric Vehicles – Options & Features

The following section provides a rounded overview of electric vehicles and is provided here in this thesis to all ow the reader to get a better understanding of EV's and provides important information and new factors that future researchers may refer to for energy models and alike. Electric vehicles vary according to a number of different parameters. Table 5.3-1 below shows the different variations of AFV's available with their drivetrain configurations, electric range and the grams of CO_2 per km for an example of that particular type of vehicle.

Table 5.3-1. Electric Vehicle Types

Type	**Drivetrain Configuration**	**Range (km)**	**gCO_2/km (WLTP[1])**
PHEV (Plug-in Hybrid Electric Vehicle)	ICE (Internal combustion engine) & chargeable electric engine powering wheels	48-64 electric	46 (Mitsubishi Outlander PHEV)
E-REV (Extended-Range Electric Vehicle)	All electric with ICE generator support for the battery	112-350 electric	0 (Battery only) / 162 (BMW i3 Empty Battery)
BEV (Battery Electric Vehicle)	All electric	128-400 electric	0
HEV (Hybrid Electric Vehicle)	ICE with additional support of electric engine, internally charged	8-32 electric	98 (Suzuki Ignis 1.2 SZ5)
FCEV (Fuel Cell Electric Vehicle)	Fuel cell providing power to electric engine and battery for energy storage	480-640 electric (with hydrogen fuel)	0

Three different plug-in vehicles exist today that consumers can choose between to suit their needs.

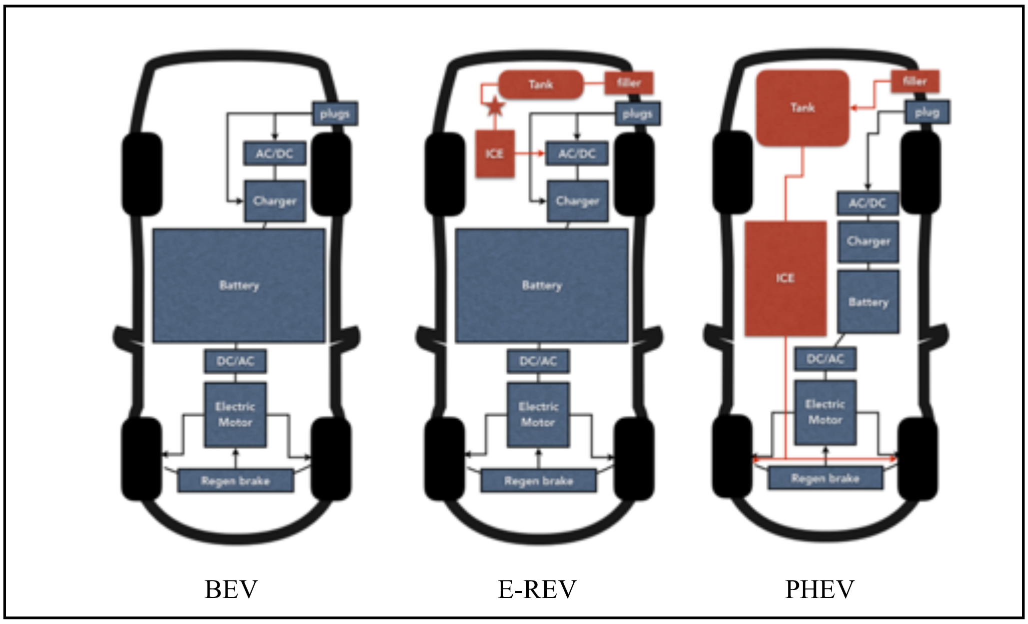


Figure 5.3.1 Conventional layouts for the typical Electric Vehicles in the market currently.

(Onewedge 2018)

The Plug-in hybrid electric vehicles (PHEV), the Extended-range Electric Vehicle (E-REV) and the Battery Electric Vehicle (BEV). The basic design premise can be seen in Figure 5.3.1. The Plug-in hybrid electric vehicles (PHEV's) contain a conventional combustion engine alongside an electric engine. The two can work together or independently often each engine powering a separate axle. This type of vehicle can provide a reduction in both transportation costs and greenhouse gas emissions when compared to a comparable conventional vehicle as when in electric mode they create zero direct emissions. The PHEV's have the capability of an electric vehicle such as charging from a regular power outlet with the added benefit of a gasoline powered engine for long distance trips. The electrical engine can operate in two different modes, Charge Depleting (CD) mode or Charge Sustaining (CS) mode (Arslan et al. 2015). The CD mode is when the vehicle uses the electric motor to generate the necessary power using the batteries as a power supply. Once the battery is depleted the PHEV will then switch to the CS mode. In this mode the vehicle uses the combustion engine to generate the required power, however while in this mode the combustion engine also generates enough energy to recharge the vehicles battery supply while driving. Typically, the battery will never reach zero charge in order to prolong battery life. PHEV's can be refuelled at regular fuel stations similar to conventional cars and can be charged at designated charging points or at regular power outlets similar to the BEV's. Some examples of a PHEV include the Mitsubishi Outlander PHEV, Chevrolet Volt, BMW-i8, Toyota Prius, Volvo V70 PHEV, Honda Accord Plug-in Hybrid, and Porsche Panamera S E-Hybrid.

Extended-range electric vehicles or E-REV's have a plug-in battery pack and electric motor as well as a combustion engine much like PHEV's. However, the difference is that in the E-REV's the electric motor always drives the wheels, with the internal combustion engine acting as a generator to supply power to the battery when it is depleted. As such, small combustion engines with low fuel consumption can be used as they are solely used to generate electricity for the E-REV's motors, as a result these vehicles are capable of long ranges between refuelling. There are multiple generations of combustions engines designed to operate the generator for the electric motor. The first generations were designed with combustion engines used by normal convention vehicles. Generation 2 is where new engines were designed to develop a fairly constant load suited to the generator for the electric motor (Sumper et Baggini 2012). The most recent development includes micro turbines and fuel cells which provide a constant load and are most suited to the electric generators needs where a constant load is favoured. Micro turbines present a real opportunity for many domestic and commercial users. Several Buses have recently been developed adopting this extended range vehicle with micro turbines and can see large improvements. For example, Capstone have developed this turbine technology and are currently market leaders in the area (Capstone Turbines Technology 2017). An example of a E-REV is the BMW i3 REX.

Battery Electric Vehicles or BEV's are the traditional electric vehicles. They have been around since the mid-19th century providing a preferred method of transport over the traditional combustion engines at the time. A BEV relies entirely on electricity for fuel and as a consequence, direct emissions are zero, typically their range is around 100-200miles. They are wholly driven by an electric motor which receives its power from a lithium-ion battery which can be charged. Electric motors are very simple when compared to the traditional combustion engine and can achieve very high efficiencies of around 95% (AEA 2008; JEC 2011). They can provide very high torque from rest and they remove the need for gearboxes and torque converters. The UK's top selling BEV is the Nissan Leaf with 20,000 units sold as of July 2017 (Nissan News 2017).

One of the big drawbacks with BEV technology is the range limitation (Graham-Rowe et al 2012), however recent technological advances could see this problem nullified. Wireless inductive charging is being introduced reducing charging times for users. However, if this technology can be introduced on the roads then it opens up an opportunity called dynamic charging, this is expanded upon in the Charging section. BEV's are completely emission-free (except brake and tire wear) and perceived as more silent in operation and are becoming increasingly viable for organisations and businesses. CEP and pharmaceutics services typically deliver in regionally limited areas, with their average daily distance range below 140km (Afroditi et al., 2014). Other businesses such as FedEx and taxi companies are now also incorporating electric vehicles into their fleets. Though, one major drawback is their cost competitiveness when compared to conventional vehicles/trucks. Davis et Figliozzi (2013) conducted a study in the U.S. using three types of electric delivery trucks in order to examine their competitiveness to conventional trucks under varying scenarios. The study showed that electric trucks can be competitive in case the cost savings from the reduced operational cost are enough to overcome the significantly high purchase costs. However, the authors did not include in their study an important factor namely the charging cost infrastructure that will be needed to be installed in order to facilitate the extra demand on the charging network.

The parallel hybrid car (or conventional hybrid HEV) which has an internal combustion engine as well as an electric motor that are both connected to the wheels proved to be a good compromise for the range anxieties that arise from BEV's. In the conventional hybrid case the electric battery is charged up using the internal combustion engine and regenerative braking, however either engine or both can be powering the wheels at one specific time. This can then be used for short range electric driving before the internal combustion engine takes over. Optimising time spent using this electric energy is a crucial way to improve efficiency in the conventional hybrids. These vehicles benefit from regenerative braking as well as weight savings over the BEV's which can play a large role in energy consumption. Due to the configuration and the fact that both engines can power the wheels they can be equipped with smaller engines, increasing efficiency. Typically, HEV's have smaller battery packs ranging from 5-10kwh, due to the fact they need to be charged and discharged quickly and frequently. Although HEV's can be complex due to their nature of two systems constantly trying to cooperate and work together to provide a desired torque value. Their basic layout is shown in Figure 5.3.2.

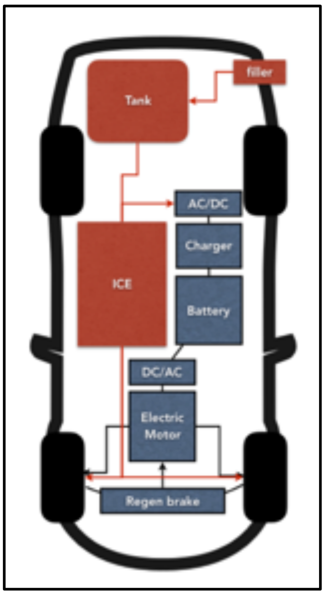


Figure 5.3.2 Conventional layouts for Hybrids Vehicles (Onewedge 2018)

The Fuel cell electric vehicles or FCEVs is a popular topic among researchers at the moment due to its potential benefits. They are predominantly powered by hydrogen with the only by-product of water vapour and warm air. Their basic layout can be shown in Figure 5.3.3. Similar to traditional combustion vehicles they can be refilled in less than 10 minutes with a driving range of around 300 miles. They work in a similar way to that of the BEV's by using electricity to power an electric motor produced by a hydrogen fuel cell. A Fuel cell is a device that takes stored chemical energy into electrical energy directly. The chemical energy that is stored between the fuels such as hydrogen, methane and gasoline is taken through two electro chemical reactions where it is converted directly into electricity. The major components of the fuel cell are the Electrolyte which also acts as a separator that keeps the reactants from mixing together. The next are the Electrodes. These are catalysts made of graphite where the electro chemical reactions occur. These are contained within a Bipolar plate (also known as a separator) which allows the current to be collected and voltage to be built from the cell. The most efficient fuel is Hydrogen due to the ease which the element can form ions. The gas is highly combustible and has a high energy content. However, hydrogen in its pure form is not readily available like conventional fossil fuels. Typically, their efficiencies are in the 60-64% range (AEA 2008). There are cells which look at taking gasoline and converting them into hydrogen rich streams to run fuel cells however the process is very complex and so designers and technicians are less attracted. Due to hydrogens low density the design of the on-board hydrogen storage systems are becoming a design challenge. The volume of the fuel cell is relatively large compared to the internal volume of a combustion engine and so fitment inside a vehicle is difficult, through technology for smaller packing of the fuel cell or more efficient packing. At room temperature and pressure, the equivalent energy contained in a petrol tank would require a hydrogen tank around 800 times the volume. In order to combat this, the hydrogen is pressurized up to 7000 times that of atmospheric pressure. At these pressures cryogenic systems have to be incorporated in order to effectively cool and liquefy the Hydrogen, Metal-hydrides are also used. These metal alloys absorb the hydrogen when under high pressures.

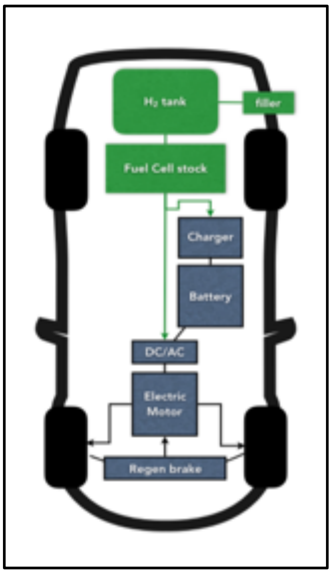


Figure 5.3.3 Layout of the Fuel-Cell Electric Vehicle (FCEV) (Onewedge 2018)

5.3.1 Battery Relevance

The batteries found in BEV's vary massively according to the role that they need to fulfil and the environment in which they are used and play a vital role in of a BEV. Energy density is a key factor when considering battery types as a higher energy density allows more energy to be stored in a smaller battery ultimately improving efficiencies. Battery energy densities are constantly improving allowing longer ranges within electrically powered vehicles. The most popular UK EV, the Nissan leaf, uses lithium ion manganese batteries providing moderate to high energy density with relatively low internal resistance. The longer-range and more expensive Tesla uses lithium ion cobalt batteries which take slightly longer to charge but typically have a higher energy density. The manganese-based Li-ion batteries chosen for the Nissan Leaf and other EVs have excellent lab results. Manufacturers also choose their batteries based on cost, some batteries are more suited for keeping the battery at high voltage and elevated temperatures than others. In some cases, as the CE tests reveal, these two conditions can cause more damage than cycling (Battery University 2016). Table 5.3.2 provides the reader with a comprehensive overview of the various types of batteries used by manufacturers today.

From Table 5.3-2, it can be seen how not only these energy densities vary from different battery types but also a vast number of alternative factors that all have a key role in the decision on which to select for its purpose. Information such as that in Table 5.3.2 can be imported into transport systems allowing the optimum conditions for various vehicles to be met when modelling to ensure correct charging/running procedures. Just as engine maintenance is important for a combustion engine, battery health is of great importance for Li-ion batteries. Although maintenance is not required, they do have a limited life cycle of around 500-1000 charges before degradation can appear. The four suspected factors responsible for capacity loss and the eventual end-of-life of the Li-ion battery are as follows:

- Mechanical degradation of electrodes or loss of stack pressure in pouch-type cells. Careful cell design and correct electrolyte additives minimize this cause.
- Growth of solid electrolyte interface (SEI) on the anode. A barrier forms that obstructs the interaction with graphite, resulting in an increase of internal resistance. SEI is seen as a

cause for capacity loss in most graphite-based Li-ion when keeping the charge voltage below 3.92V/cell. Electrolyte additives reduce some of the effect.

- Formation of electrolyte oxidation at the cathode that may lead to a sudden capacity loss. Keeping the cells at a voltage above 4.10V/cell and at an elevated temperature promotes this phenomenon.
- Lithium-plating on the surface of the anode caused by high charging rates. (Elevated capacity loss at higher C-rates might be caused by this.)

Table 5.3-2 Battery Specifications (Battery University 2018)

Specifications	Lead Acid	NiCd	NiMH	Li-ion		
				Cobalt	Manganese	Phosphate
Specific Energy Density(Wh/kg)	30-50	45-80	60-120	150-190	100-135	90-120
Internal Resistance (mΩ)	<100 12V pack	100-200 6V pack	200-300 6V pack	150-300 7.2V	25-75 per cell	25-50 per cell
Life Cycle (80% discharge)	200-300	1000	300-500	500-1,000	500-1,000	1,000-2,000
Fast-Charge Time	8-16h	1h typical	2-4h	2-4h	1h or less	1h or less
Overcharge Tolerance	High	Moderate	Low	Low. Cannot tolerate trickle charge		
Self-Discharge/month(room temp)	5%	20%	30%	<10%		
Cell Voltage (nominal)	2V	1.2V	1.2V	3.6V	3.8V	3.3V
Charge Cut-off Voltage(V/cell)	2.4 Float 2.25	Full charge detection by voltage signature		4.2		3.6
Discharge Cut-off Voltage(V/cell, 1C)	1.75	1		2.50-3.00		2.8
Peak Load Current	5C	20C	5C	>3C	>30C	>30C
Best Result	0.2C	1C	0.5C	<1C	<10C	<10C
Charge Temperature	-20 to 50°C -4 to 122°F	0 to 45°C 32 to 113°F		0 to 45°C 32 to 113°F		
Discharge Temperature	-20 to 50°C -4 to 122°F	-20 to 65°C -4 to 149°F		-20 to 60°C -4 to 140°F		
Maintenance Requirement	3-6 Months (topping charge)	30-60 days (discharge)	60-90 days (discharge)	Not required		
Safety Requirements	Thermally stable	Thermally stable, fuse protection common		Protection circuit mandatory		
In Use Since	Late 1800s	1950	1990	1991	1996	1999
Toxicity	Very High	Very High	Low	Low		

Along with these factors of capacity loss, thermal management plays a key role in BEV's. As shown in Table 5.3-2, batteries have a certain operating window when charging and discharging. Temperature has a large importance on the performance of EV batteries and shouldn't be overlooked. At cold temperatures Battery performance is lower due to poor ion movement, viscosity changes result in slow electro-chemistry, see Figure 5.3.4. Resistance therefore increases with temperature effecting the relative capacity. This has a substantial effect on the range and the acceleration when compared to conventional vehicles. A low temperature affects the charging, allowing for a possible increase in dendrite creation. The low temperature also has a profound effect when the heaters are used due to the smaller EV range the increase in energy output results in a higher energy loss compared to a conventional vehicle. For example, in cold weather conditions the effect of the heater can nearly double the energy consumption and cut the range in half when using specific driving cycles. Table 5.3-3 provides the reader with average reductions in range for common vehicle functions. With an already limited range additional auxiliary functions can limit the range of BEV's further. As a result, they can have a seriously reduced range in cold/hot weathers when additional auxiliary functions such as cabin heaters or A/C are used.

Table 5.3-3 Impact of equipment on EV Performance (EV Auxiliary Systems Impact 2018)

Accessory	Range Impacts	Comments
Air Conditioning	Up to 30%	Highly dependent on cabin temperature, ambient temperature and air volume
Heating	Up to 35%	Highly dependent on cabin temperature and ambient temperature.
Power Steering	Up to 5%	Necessity
Power Brakes	Up to 5%	Necessity
Defroster	Up to 5%	Depending on use
Other – Lights, Radio, Phone, Power-assisted seats, windows, locks etc.	Up to 5%	Depending on use

It is therefore important that these factors need to be taken into account when planning electric vehicle routes as they can affect the range by a large amount. Powertrain efficiencies of BEV's are higher compared to the engine powered counterparts making the accessory loads more significant for some driving styles. One crucial aspect that needs highlighting is the hot climate environment. At Hot temperatures the battery can become in danger of degradation and at extremely high temperatures can cause serious harm with thermal runaway, a process in which the battery starts causing reactions within the battery that create further reactions eventually ending up with the battery exploding. Although manufacturers introduced strict thermal management practices within their production of their vehicles EV's batteries still rise significantly during the charging process. The effect is more profound when fast charging, in order to minimize degradation battery operating temperature should be kept between 15 and 35 degrees Celsius. This can be monitored on all BEV's vehicles and often BEV's limit their charging speeds according to the battery temperature. Figure 5.3.4 shows a graph demonstrating the effect thermal management plays on battery life in a reader friendly format.

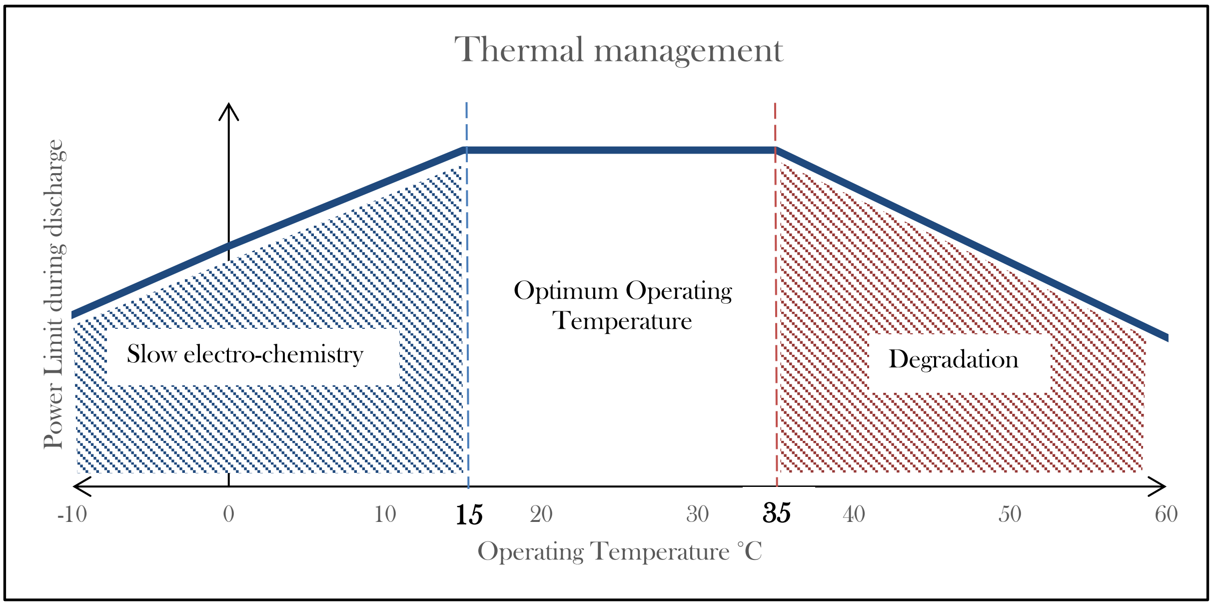


Figure 5.3.4 Thermal Management for Lithium-Ion Batteries in an EV. (This graph was created based on data found here: http://www.nrel.gov/docs/fy13osti/58145.pdf)

5.3.2 Charging implications

One main influencing factor on the temperature of the battery is charging. The speed at which a vehicle is charged is directly related to its temperature. Manufacturers that use large batteries often employ battery cooling techniques to allow the batteries to still charge at a fast rate without thermal management issues. Charging can also be negatively affected due to microscopic fibres of lithium, called "dendrites," growing on the cathodes. Dendrite growth is progressively worse with increase in the reacting surface area. The reaction process is accelerated by almost a factor of 10 in worse case scenarios at -20 degrees. Future developments in the design of batteries show that we could be heading towards the use of ultracapacitors as well. Ultracapacitors can store significantly more charge than regular capacitors due to the effective material used in their production, they can also be charged more than 1 million times meaning they could provide a viable solution to electric vehicle distance anxiety. Combining the two can protect from surges in the fuel cells proving excellent power and energy density (NASA 2010).

Charging Types - There are three main EV charger types that are currently in use:

- Slow: these slow charging units provide up to 3kW and are best suited for overnight charges as a full charge on a typical vehicle can take anywhere between 6-8 hours.
- Fast: these chargers provide between 7-22kW of power which offers charging times between 3-4 hours.
- Rapid: these charging units are the most powerful and provide 45-50kW, capable of providing vehicles with an 80% charge in as little as 15-30mins. These charging points come in two different variants, AC and DC.

The number of charging points has been steadily increasing in the UK with just over 9000 points as of September 2015 and over 19000 as of January 2019 (Zap- Map 2019), with many more planned to be installed by the UK government as the electric vehicle market increases. Slow chargers use (in most cases) a standard single phase 13A three-pin plug, the very first charging points installed were of this type, however they are now being replaced by Fast and Rapid charge points. Almost every vehicle can be slow charged with each vehicle provided with a standard 3-pin plug at the charging point outlet and a Type-1 (J1772) or 7-pin Type 2 (Mennekes) connector for the vehicle inlet. Fast chargers reduce the rate of the slow charger times significantly; this is accomplished by doubling the available Amperes to 32A or 7kW for a single phase. This type of charger is the most commonly installed with over 5500 installed in the UK as of September 2015. For larger commercial vehicles such as trucks and buses fast 3-phase charging is available capable of delivering 22kW in total.

Rapid chargers, while growing in popularity, are relatively new. They come equipped with a tethered cable with a non-removable connector coupled with an inlet socket. The AC variants are the least popular due to only a few UK EV's models designed to accept them. Rapid AC charger are rated at 63A, 43kW (3-phase) using high power alternating current (AC) supply's, and the Type 2 (Mennekes) connector. The DC Rapid charge variant provides high power direct current (DC) supply at 125A, 50kW. These DC rapid chargers are fitted with either a JEVS (CHAdeMO) or a 9-pin CCS (Combo) connector. Around 1500 Rapid chargers are currently installed in the UK (as of beginning of 2016). As mentioned previously due to the high amperage of this form of charging the internal battery temperature increases dramatically, with frequent rapid charging/discharging this has more bearing. When charged at a fast rate, dendrites appear from the surface of the lithium electrode and spread across the electrolyte until they reach the other electrode. An electrical current passing through these dendrites can possibly short-circuit the battery, causing it to rapidly overheat and in some instances catch fire. Efforts to solve this fairly new problem by inhibiting dendrite growth have been met with limited success (Lithium ion roots).

Nissan are one of the leaders in electric vehicles. They have two globally market Electric Vehicles one being the Nissan Leaf designed for public use with the 2016 model providing an EPA-estimated 107 mile range (but a large 155 mile range according to the new European driving style), with the 2019 model anticipated to have an EPA range of over 225miles. The other the e-NV200, a short wheel based commercial van, aimed at businesses with a similar range of 106 miles with 4.2m^3 of loading space and a loading bay of 2.04m. Both vehicles use the same charging modes and require similar charging times. 8 hours on the slow 3kw charger, 4 hours on the fast 7kw chargers and capable of an 80% charge in 30mins using the rapid charge. These rapid chargers mean that these electric vans can be viable solutions to logistic firms wanting to reduce their overall carbon footprint. The cost of charging cannot be written off however, and as the infrastructure improves and more companies are offering charging so will come price variations of charging. The current market leader for electric charging stations is Ecotricity with the most comprehensive charging network in Europe (Ecotricity 2016). The price for a 30-minute rapid charge (43kw AC up to 50kw DC) is around £6 providing up to 80% charge depending on battery capacity. However, for home/business use on personal electricity the society of motor manufacturers (SMMT) say that the typical cost of electricity to charge an EV is approximately 3p per mile, compared with petrol/diesel costs of around 16p per mile. This value was calculated when recharging times were considered to be at night, when energy is largely subsidised (Schönewolf 2011). As mentioned before the battery's themselves can suffer from degradation from over charging. Bashash et al. (2011) provide an optimal charge pattern plan for plug in hybrid vehicles however the premise can be carried across to BEV's also. The paper looks at the total cost of electricity and fuel and the total battery degradation over a 24h period. Among researchers the common definition for the battery's end-of-life is around 70-80% of its original energy. However, researchers have found that this value can be significantly less in real life situations due to most people not driving more than 40 miles per day Saxena et al. (2015), the authors suggest using an alternative metric of defining battery retirement when it no longer meets the daily travel needs of a driver. Botsford et Szczepanek (2009) investigate the issues facing widespread use of electric vehicles. The study shows an example of how limiting only slow charging can be and how rapid chargers could help with adoption of EV's.

During charging BEV's do not necessarily need to be fully charged before leaving the charging station. Goeke et Schneider (2014) use a full maximum charging system at a constant rate, in their electric vehicle routing problem with time windows and mixed fleet. The mixed fleet contains both combustion and electric vehicles. Keskin et Catay (2016) relax the full recharge restriction and allow partial recharging, which is more practical in the real world due to the shorter recharging duration. The results highlight that the partial recharging may significantly improve routing decisions. Specifically, they modeled charging time as a function of the SOC of the battery. Table 5.3-3 shows the results from running common EV functions. The results were based upon the popular Nissan leaf BEV. For full leaf information the reader is directed to (Nissan Leaf Specs 2016).

Dynamic charging could allow electric vehicles to charge while they are driving. A localised electromagnetic field is created between the charging pad on the electric vehicle and the corresponding charging pad in the road and a current induced charging the battery. Although still in its infancy, the technology is there and would have worthy benefits in applications such as traffic queues and traffic lights etc. The use of lithium ion batteries will significantly minimize the emissions however there is a limited amount of lithium and the future of the BEV's could be unknown. On-line electric Vehicles (OLEV's) draw their power from electric coils that are underground wirelessly (Suh 2011). Su et al. (2015) look at how the infrastructure supports wireless inductive charging for OLEV's in Korea analysing the benefits of the dynamic charging with an economic model of the battery size and the required charging infrastructure. With dynamic charging EV's can charge more often and so smaller batteries can be used in operation (Lukic et Pantic 2013). Using real-life data the authors found that although a larger initial cost for installation was needed for dynamic charging more cost saving can be accomplished by extending battery life. Future steps within the electric vehicle routing problem could identify these dynamic chargers using a stochastic charging model. Another novel idea that is proving increasing popular among researchers is the possibility of Battery swapping, where depleted batteries from electric vehicles can be exchanged for recharged ones on long trips (Brown et al. 2010; Yang et Sun 2015; Zheng et al. 2013). The success depends upon the infrastructure of the swapping stations and the ease of service.

5.3.3 Relevance of Regenerative Braking technology

EV's mostly employ regenerative braking technology. This allows the vehicles to convert Kinect energy into electrical energy which can then be stored in the battery when slowing or travelling down a decline. The electric motor functions as a generator, supplying the battery with the electrical energy generated. Regenerative braking also brings with it additional benefits such as reduced brake wear and the ability to use one pedal when driving, also known as an e-pedal. Single pedal driving is a relatively new concept although allows regenerative braking to be used to its full potential. When the user fully releases the pedal the vehicle is in the maximum regeneration mode. This acts just as normal combustion engine brakes would and stop the car with considerable force. When the user wishes to come to a gradual stop then the pedal is released partially and a % of regenerative braking force is used instead.

5.4 Emissions

When determining the emissions generated from a vehicle a three-scope approach can be used. This is a widely-accepted approach used here to identify and categorize emissions-releasing activities into three groups known as scopes. Each activity is listed as either Scope 1, Scope 2 or Scope 3, more information on how the Scopes are used, as well as all other aspects of reporting, can be found in the Greenhouse Gas Protocol Corporate Standard (Gov.uk).

- Scope 1 (Direct emissions): Emissions from activities owned or controlled by an organization. Examples of Scope 1 emissions include emissions from combustion in owned or controlled boilers, furnaces, vehicles; emissions from chemical production in owned or controlled process equipment.
- Scope 2 (Energy indirect): Emissions released into the atmosphere associated with the consumption of purchased electricity, heat, steam and cooling. These are indirect

emissions that are a consequence of an organization's energy use but which occur at sources they do not own or control.

- Scope 3 (Other indirect): Emissions that are a consequence of your actions, which occur at sources which you do not own or control and which are not classed as Scope 2 emissions. Examples of Scope 3 emissions are business travel by means not owned or controlled by your organisation, waste disposal which is not owned or controlled, or purchased materials or fuels. Deciding if emissions from a vehicle, office or factory that you use is Scope 1 or Scope 3 may depend on how you define your operational boundaries. Scope 3 emissions can be from activities either upstream or downstream from an organisation.

The generated emissions for scope 1 of various types of conventional vehicle can be found in Table 5.4.1. Passenger cars conversion factors are related to the market segments specifically defined by SMMT (UK Society of Motor Manufacturers and Traders). The conversion factors are based in information generated from the department for transport, who regularly analyses the mix of cars on the road using number plate recognition. The CO_2 emissions generated from these AFV's are significantly less than their diesel and petrol counterparts, 44% and 46% respectively. AFV's play a key role in the quest to reduce emissions. Traditional petroleum based powered vehicles produce many emissions mainly at scope 1. The emissions generated by these vehicles and their effects on humans are explained in detail within section 2.4 alongside the UK emissions. Scope 1 emissions from these petroleum-based vehicles are not only harmful for the environment but also people. Direct tailpipe emissions can lead to Air pollution, NO2 and PM exceedances in cities are becoming increasingly common. Congested traffic poses a real threat to air quality and It is well known that road transport in the urban area is a major source of air pollution across the world. Though in Europe all the vehicles have to comply with the EU emission standards. The emissions are tested using the legislated standard driving cycles. Unfortunately, these often do not represent real world driving emissions. This is because compared to the legislated driving cycle, real-world driving uses different engine power configurations, differing speeds, different acceleration rates, varying traffic congestion, continuously changing road gradients, different cold start conditions, various numbers of stop/start events all occurring with varying weather conditions; the outcome will inevitably result in different emissions. The true emissions generated by these petroleum-based vehicles is actually very different than the emissions calculated on these driving cycle tests. It is therefore important that we must address the air pollution in these urban areas. BEV's generate zero emissions and therefore make great candidates for heavily urban areas where traffic congestion is a major issue and range is also less important due to reduced driving distances in cities, increased congestion and reduced speed limits. Although BEV's generate little to no emissions, indirect emissions must also be considered. The Electric vehicles emissions are classified as mainly Scope 2 and are directly related to the fuel mix that is used to create the electricity. As mentioned previously the UK's Power sector has reduced their emissions drastically, this is directly proportional to the emissions generated by BEV'S. The emissions do however also depend on other factors the type of day, where different combinations of power sources are used. With the recent technological advancements mentioned previously such as autonomous vehicles, dynamic charging, and reduced charging times it opens us a wider range of emission reducing possibilities. With faster charging the vehicles are suitable for longer range drivers allowing minimal stopping times allowing EV driving to appeal to a wider audience. With the introduction of dynamic charging streets in cities that are normally filled with idling vehicles can now be replaced by electric vehicles wirelessly charging while on the move, leading to a significant reduction in urban air pollution. Autonomous electric vehicles help optimise the charging times and can charge themselves when the national grid is at its least demand, meaning just green energy production is needed to meet demands. This in turn allows BEV's to charge at zero scope 2 pollution, this aspect is covered in more detail in the following section.

Table 5.4-1 Average new car CO2 Emissions and Registrations (New Car CO2 Report 2018)

CO2 g/km (sales weighted average)		2000	2007	2016	2017	2017 v 2016	2017 v 2000
	Total Market	**181**	**164.9**	**120.2**	**121**	**0.8%**	**-33.1%**
	Registrations ('000s)	2222	2404	2693	2541	-5.7%	14.4%
BY FUEL TYPE	**Diesel**	**167.7**	**164.3**	**120.1**	**122**	**1.6%**	**-27.3%**
	Registrations ('000s)	313	967	1285	1066	-17.1%	240.3%
	Petrol	**183.2**	**165.7**	**123.7**	**125**	**1.1%**	**-31.8%**
	Registrations ('000s)	1908	1420	1319	1355	2.7%	-29.0%
	AFV	**127.3**	**127**	**66.8**	**67.5**	**1.0%**	**-47.0%**
	Registrations ('000s)	0	17	89	120	34.8%	33454.0%
BY SALES TYPE (STARTS 2001)	**Private**	**176.4**	**165.8**	**122.3**	**122.7**	**0.3%**	**-30.4%**
	Registrations ('000s)	1212	1046	1206	1124	-6.8%	-7.2%
	Fleet	**175.4**	**164**	**118.3**	**119.8**	**1.3%**	**-31.7%**
	Registrations ('000s)	1031	1195	1381	1319	-4.5%	27.9%
	Business	**195**	**165.9**	**119**	**118.8**	**-0.2%**	**-39.1%**
	Registrations ('000s)	214	163	106	98	-7.8%	-54.5%
BY SEGMENT	**Mini**	**153.8**	**128.5**	**105.5**	**105.9**	**0.4%**	**-31.2%**
	Registrations ('000s)	52	22	77	69	-10.1%	31.9%
	Supermini	**152.9**	**141.8**	**111.1**	**110.7**	**-0.4%**	**-27.6%**
	Registrations ('000s)	689	771	873	748	-14.3%	8.7%
	Lower Medium	**175.3**	**158.6**	**114.8**	**115.8**	**0.9%**	**-34.0%**
	Registrations ('000s)	662	722	735	728	-0.9%	10.1%
	Upper Medium	**192.4**	**169.1**	**119**	**120.5**	**1.3%**	**-37.4%**
	Registrations ('000s)	477	386	257	243	-5.4%	-49.1%
	Executive	**235.6**	**192.6**	**120.8**	**121.6**	**0.7%**	**-48.4%**
	Registrations ('000s)	105	104	128	123	-3.6%	17.8%
	Luxury	**292.3**	**273.8**	**182.4**	**178.9**	**-1.9%**	**-38.8%**
	Registrations ('000s)	11	13	11	9	-12.5%	-19.4%
	Sports	**220.5**	**224**	**161.4**	**155**	**-4.0%**	**-29.7%**
	Registrations ('000s)	67	66	50	48	-4.5%	-29.2%
	Dual Purpose	**259.4**	**228.3**	**141.4**	**141.3**	**-0.1%**	**-45.5%**
	Registrations ('000s)	99	176	438	460	5.1%	364.1%
	MPV	**211**	**179.7**	**128.7**	**132**	**2.6%**	**-37.4%**
	Registrations ('000s)	60	143	125	112	-10.7%	86.8%

5.4.1 UK Transport Emissions and the Impact of BEV's

All vehicles generate emissions whether directly or indirectly. With an increasing number of vehicles being registered each year within the UK, advancements in engine technology and emission reduction hardware are critical. The UK government have their sights firmly on reducing transport pollution within the UK focussing on urban areas such as London (Ulez 2018). The government have brought in a ban on all new petrol and diesel cars from the year 2040 which has recently been brought forward to 2030 by UK mayors (Sadiq 2018). Along with a £255 million fund to help councils tackle emissions its clear to see the emphasis the leading officials are placing on improving the air quality around our streets. The UK vehicles and LGVs and HGVS travelled a combined 60.9 Billion miles in 2014, an increase of 5.5% and 2.0% respectively (Great 2014). Using the department for statistics average fuel consumption (LGV – 13.6 mpg, HGV – 7.9mpg) this mileage equates to 5.32 billion gallons of fuel. This amounts to 64.8 million tonnes of CO_2. This is a huge amount of potential pollution that is being created. The use of alternative methods of transport could reduce this amount with electric vehicles being a viable way forward. For more detailed breakdowns of the CO_2 generated by engine type the reader is referred to Table 6.2.1 in Appendix.

With most goods vehicles currently in the market being diesel, in this section we will focus on these combustion engine types rather than petroleum fuelled combustion engines. We then go on to discuss future engines with electric vehicles and ultra-low emissions vehicles. Diesel vehicles are very common in medium to heavy goods vehicles, and also popular amongst the public due to their longer driving range, higher engine efficiency, low running costs and durability when compared with their petrol counterparts. However, they have recently seen a big drop off in sales. March 2018 saw a 37% reduction with the previous year (New Vehicle Registrations 2018). Recent emissions scandals whereby companies such as VW were found to be using emissions cheating devices built into the engine control unit have cause a lot of doubts around the actual emissions generated by these diesel engines (Autocar 2015; Scandal 2016). The vehicle could sense when it was under test conditions and employ all of its available emissions reduction systems to reduce the emissions to below the required limit. When under normal driving conditions on the road some of these systems were not working as effectively, this provided an enhanced driver experience with better performance but increased emissions. Running without the device the vehicles were found to be producing around 40 times the allowed amount of nitrogen oxide in the U.S. The result of the scandal was dramatic, VW group was issued a fine around £4.7 billion with the possibility of a maximum fine of £13.7 billion however this figure does not include the cost of repairing the vehicles. As a result, the company's shares dropped by 30% in the short period following the scandal. The increased emissions dramatically affect the environment with the vehicles in the U.S creating between 10,392 – 41,571 tonnes of toxic gas into the air each year, rather than the expected 1,039 tonnes of NO_x (Scandal 2016). Recently, however it has been found that other manufacturers including Mercedes have also been found guilty of having emissions defeat devices fitted and are now recalling over 770,000 vehicles (BBC News 2018). There are seven main Greenhouse Gases (GHGs) that contribute to climate change, as covered by the Kyoto Protocol: carbon dioxide (CO_2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF6) and nitrogen trifluoride (NF3). Different activities emit different gases. GHG emissions from transport have been fluctuating over the last two decades, although remained fairly stagnant over the last 4 years. The government aims to reduce CO_2 levels by 80% by the year 2050 (ULEV 2015). Other than increase in technology and advances in transport the government adopts various policies to try and reduce the overall impact. Some research carried out by the government includes looking at various scenarios and how they will affect the GHG emissions within the transport sector. Figure 5.4.1 shows how these policies will affect the emissions.

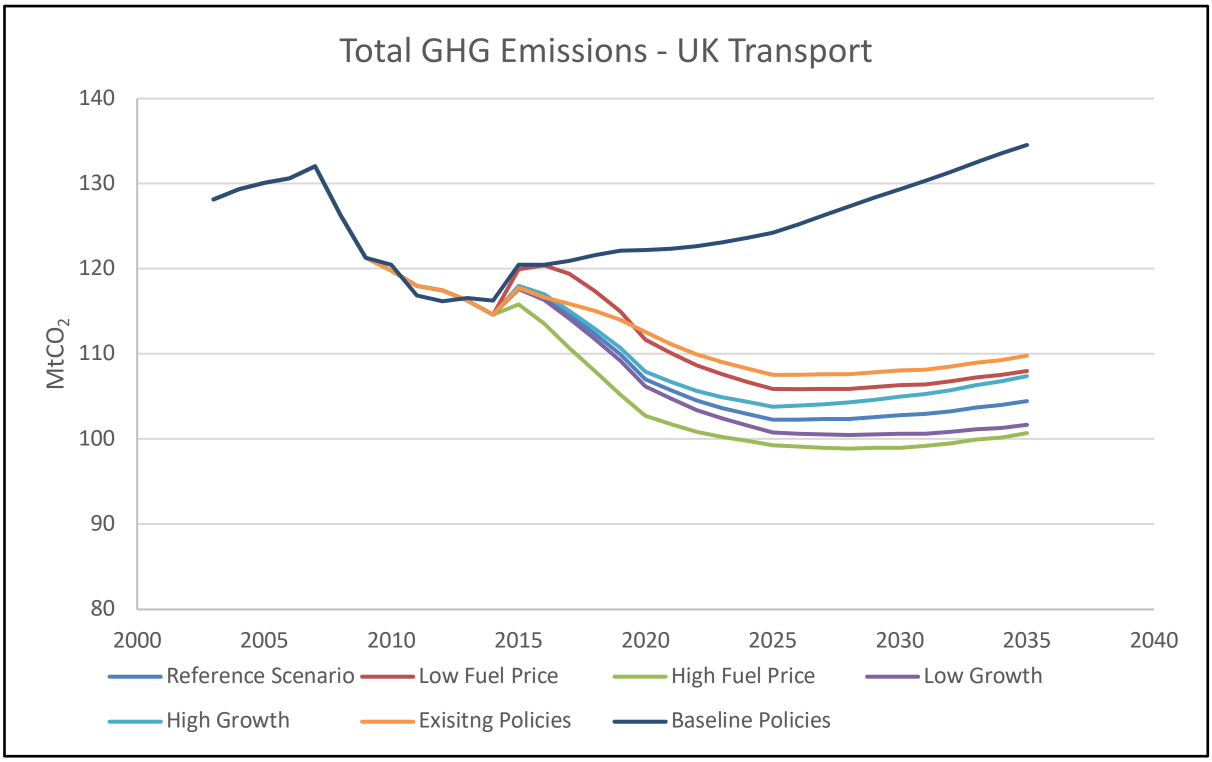


Figure 5.4.1 How policies will change the total GHG emissions (Road transport and Environment 2016)

It can be seen that if only baseline policies were met the estimated emissions increases. The baseline reference is based on central estimates of economic growth and fossil fuel prices and indicates further actions must be taken to reduce CO_2. As it can be seen from the graph fuel price has a vital role in the reduction of emissions. With a low fuel price, consumers are more likely to use their tradition combustion engine vehicle resulting in increased pollution. On the other hand, a high fuel price can be the main factor in reducing emissions, this will drive people to alternative fuel powered vehicles and alternative means of transport. These alternative fuel vehicles must still be monitored carefully as they are not emission free.

When diesel combusts, it emits many different pollutants of which several are very harmful. During the combustion process fuel is injected at very high pressures, this is then put under immense compression during the combustion stroke of the engine, generating the required heat to cause the diesel fuel to ignite. In an ideal environment with exceptionally high combustion efficiencies the bi-product of the combustion would be only CO_2 and H_2O (Prasad et Bella 2010). However, factors such as combustion temperature, air-fuel ratio and turbulence in the combustion chamber reduce the efficiency and a number of harmful products are generated such as CO, PM, NO_x, SO_x and HC.

- Carbon Monoxide (CO) – produced by internal combustion engines and can lead to Carbon Monoxide poisoning, causing serious health issues and in severe cases death. (NHS 2019)
- Particulate matter (PM) – consistently associated with respiratory and cardiovascular illness and increased mortality. Diesel engine exhaust has been classified as carcinogenic to humans by the World Health Organization. Secondary PM contributes to the acidification of ecosystems.
- Nitrogen Oxides (NOx) – are a harmful pollutant generated from diesel engines which not only has detrimental effects to the environment but is also the pollutant that causes most health problems. They can cause inflammation of the airways and long-term exposure may affect lung function and respiratory symptoms. High levels can also have an adverse effect on vegetation. NOx contributes to acidification and/or eutrophication of habitats and to the formation of secondary particles and ground level ozone, both of which are associated with ill-health effects. Actions are needed to reduce this health issue for both the workers and the general population. (Sydborn et al. 2001)
- Sulphur Oxides (SOx) – causes constriction of the airways of the lung. Involved in the formation of PM. This contributes to acidification of terrestrial and aquatic ecosystems, damaging habitats and leading to biodiversity loss.
- Hydrocarbons (HC) – these are chemical compounds found on Earth and are the reason fossil fuels combust; extremely important in modern day society. Diesel fuel contains

larger Hydrocarbons molecules with more carbon atoms than petroleum, and as such has a higher fuel density. Issues arise when incomplete combustion takes place releasing emissions pollution into the atmosphere.

Diesel engines produce the highest level of these gases from their exhausts and have been shown to be linked to carcinogenetic effects which can lead to cancer of the lungs (Diesel Engine Exhaust 2012). The study conducted by the IARC was mainly composed of workers exposed to diesel exhaust gas fumes. However, in the past carcinogens that have been shown to have high risk to heavily exposed groups were also found to be present to the general public. It has been estimated that 20-70% of PM is attributed to the combustion derived particles from traffic (Gong et al. 2005; Reis et al. 2018; Rückerl et al. 2007). Diesel emissions are linked to causing inflammation and tissue damage and with chronic exposure harmful physiological changes can occur within multiple organ systems (Reis et al. 2018).

With the UK transport industry currently making up 27% of all UK GHG emissions it is of the upmost importance that we aim to reduce this negative effect. This could be achieved by identify new technology's and methods to improve the air pollution levels. In 2017 Diesel Vehicles provided a 42% market shares of new cars, on average these diesel vehicles produce 122 CO_2 g/km. By contrast AFV's provide a smaller 5% market share emitting on average just 67.5 CO_2 g/km. These figures are measured at the tailpipe to evaluate in-use emissions performance. BEV's produce zero tailpipe emissions and an increase in BEV sales will provide a crucial reduction in direct CO_2 emissions and can have a beneficial impact on the dangerous emissions emitted by combustion engines for the public. BEV's are not completely emission free however, and they can still produce emissions indirectly. Accurately understanding the emissions generated by charging the batteries can provide a further reduction in these indirect emissions.

Limited research has been carried out to calculate the emissions actually generated from ULEV's. Well-to-wheels emissions is generally used where the emissions are calculated from how the fuel is produced and the way in which the vehicle is operated. In this study centre of the focus is on BEV's however the information can easily be carried over to PHEV's as well. For more detailed information on the emissions of PHEV's the reader is directed to (Jung et Li 2018).

When compared with internal combustion engines (ICE's) EV's have many advantages including (Fiori et al. 2016):

- Greater energy efficiency through the use of on-board electric devices.
- Regenerative braking, reducing driving emissions.
- The possibility of obtaining greener fuel sources.
- Zero tailpipe emissions.
- Less noise pollution.

As already described in Section 3.3 regenerative braking allows EV's to recover energy that is normally lost in the braking phase and convert it back into stored electrical energy. This is the opposite to the case of the traditional ICE vehicle where the energy generated from braking is lost as thermal losses. Several empirical studies have shown that EV's consume less energy while driving in urban areas and are able to recover energy while braking (De Gennaro et al. 2014; Rambaldi et al. 2011). Traditionally the electric vehicle is thought of as an emission free vehicle, due to zero tailpipe emissions while on the move. However, the electricity that is needed to power the engine creates emissions on production/generation.

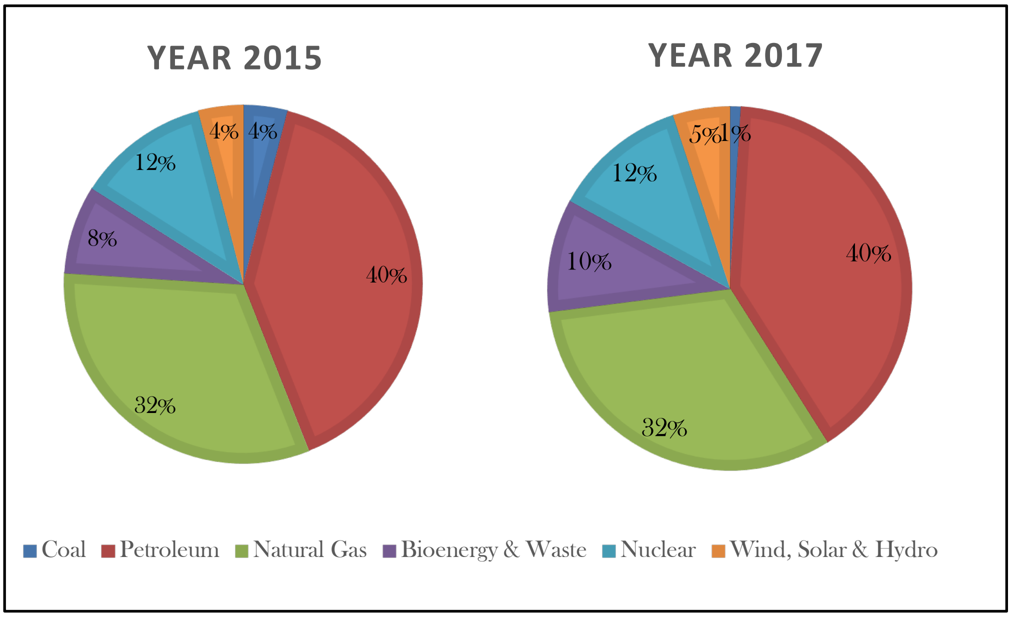


Figure 5.4.2 The Indigenous Fuel Mix for the U.K in 2015 & 2017 (Energy Trends 2019)

The amount of emissions is generally down to the fuel mix from the country of origin. The following research has taken data from the government fuel disclosure mix 2015 and 2017. The department for environment food & rural affairs (DEFRA) quotes the figure as being 0.527 kg/kWh of electricity generated. This figure is used by businesses to provide a carbon emission estimation; a requirement for plc's. The indigenous fuel mix for year 2015 and 2017 is shown in Figure 5.4.2.

The shift away from coal can be seen as can the increase in Bioenergy and waste. This shift towards a greener electricity fuel mix provides a direct reduction in BEV emissions. However due to the nature of Electric vehicles the emissions they create is entirely dependent upon the fuel mix in the country they are being used. In the combustion process of the different fuels each fossil; fuels emit differing amounts of CO_2.

The Fuel Mix for the period (01/04/2014 – 31/03/2015) can be seen in Table 5.4-2, which includes the transmission loss factor of 1.12. Please note that this is the overall energy source including energy produced from other countries hence the varying values when compared with the indigenous mix shown in Figure 5.4.3.

Using this information one can calculate the average kg of CO_2 per kWh. This equates to 0.527 kgCO_2/kWh at the time of data recording. This value represents an average emission factor of the electricity generated in the UK.

Table 5.4-2 The Fuel mix of the U.K with the estimated CO2 produced for each energy source (UK Government Fuel Mix Disclosure. 2017).

Energy Source	**Residual %**	**UK %**	**CO_2 (g/kWh)**
Coal	38.7	26.7	910
Natural Gas	36.2	29.7	380
Nuclear	14.2	22.2	0 ([2]0.007 g/kWh)
Renewables	4.6	19.3	0
Other Fuels	6.3	2.1	600

All conversion factors presented here are in units of CO_2. CO_2e this is the universal unit of measurement to indicate global warming potential (GWP) of Green Houses Gases (GHGs) expressed in terms of the GWP of one unit of carbon dioxide. The Residual % is nothing more than a grid emission factor. The residual mix incorporates the allocation of renewable energy by those who have purchased electricity tracking certificates like guarantees of origins (GOs). As it can be seen from Table 5.4-2 the emissions generated via Coal and Other Fuels produce significantly more CO_2 emissions per kWh than other sources of energy. Though, this is often the cheapest form and as such is favourable in terms of cost. However long-term effects can bring serious detrimental environmental impacts. Other sources of fuel include pumped storage as well as alternative sources of electricity generated abroad and distributed to the U.K. Although Nuclear does not produce CO_2 emissions as a direct product, there is the production of radioactive material. This is a major problem with nuclear energy and there is yet to be a viable solution to this waste problem. The UK has introduced new planning regimes for its power generation recently. These include the installation of new nuclear reactors, large wind farms, reservoirs and railways (World Nuclear 2018). However, as this study is focused on the current fuel mix, the above issues are beyond the scope of this work.

The fuel mix varies dramatically over the course of a day. Peak and off-peak grid times involve a different combination of power sources resulting in varying emissions and evidently different prices.

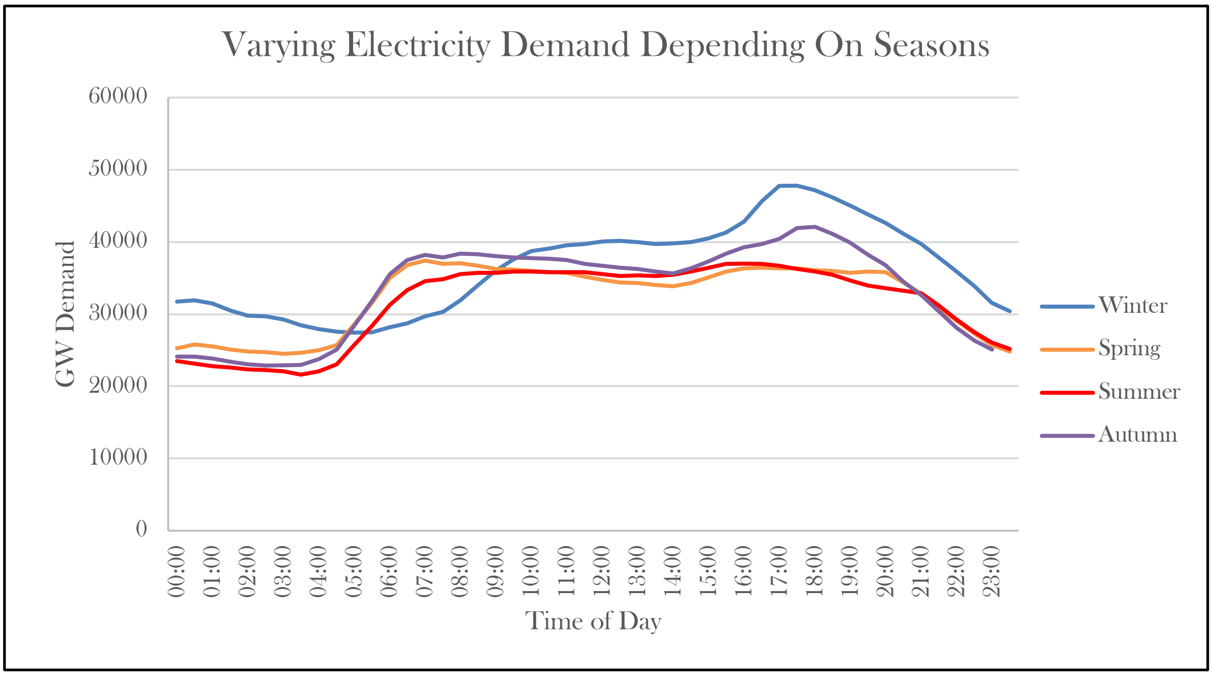


Figure 5.4.1 Varying energy demand throughout the day dependent on seasons.

Figure 5.4.4 demonstrates how much these peak loads change over the course of the day. The values are calculated from (Gridwatch 2019) using the past history for the year 2015. Each data series is the average Wednesday electricity demand during the middle of each season. Wednesday was chosen as it is half way through the normal working week providing a good estimate on the demands when routing commercial vehicles during working hours. The peak hours can be seen to be around 16:00 to 19:00 with more being generated in winter. This is due to people arriving back from work and using appliances within their homes and the need for heating in winter. As the electricity demands change throughout the day so does the energy source used to create electricity. A more detailed breakdown can be found at the renewable energy foundation (REF 2019), here the changes to the fuel mix during peak and low grid times can be seen. By looking at past data predictive models can be created to forecast the amount of emissions generated at certain times of the day generating accurate predictive emissions models for EV charging. Using this information on varying power demand shown in Figure 5.4.4 and linking to the UK fuel mix in Table 5.4.1 and emissions of those power sources an accurate emission evaluation can be achieved, we have implemented a simple breakdown of the results in Table 5.4-2 and provide an emissions cost to charge an EV with a 30kWh capacity at different times of day. Using Gridwatch (2016) historical data and averages throughout the seasons we were able to generate relevant fuel mixes for different times of the day. Charging a 30kWh electric vehicle produced the following emissions.

Table 5.4-3 Emissions generated to charge a 30kWh EV during different times throughout the day

Season	Time of Day to recharge	Emissions generated kgCO_2 for 30kWh
Winter	7:00	11.04
Summer	7:00	7.52
Winter	12:00	11.44
Summer	12:00	7.46
Winter	17:00	11.84
Summer	17:00	7.44
Winter	00:00	8.92
Summer	00:00	7.04

One can clearly see the benefits of scheduled charging when looking at the emissions generated at different periods throughout the day for the UK. The two days selected were the 30th of Jan 2019 for the winter comparison and the 1st of August for the Summer. During winter months energy consumption is much higher as can be seen in Figure 2.9, this has a direct effect on emission when charging EV's. In the case above the difference of charging your 30kWh EV at 17:00 and 00:00 in winter is a staggering 2.5kg. When looking at summer fluctuations the differences are noticeably less, and the benefits drops to 0.5kg when charging at night. Overall peak differences between the seasons can vary emissions by as much as 68%, during the day emissions can change as much as 33%. This case as mentioned is for the UK where renewable energy sources make up around 20% of the fuel mix. As this percentage is increased and electricity becomes greener the importance of charging times increases.

5.5 Cost implications

The cost of the various AFV's vary according to their type. Costs are a large influence when considering what vehicle to purchase and can often put consumers off EV's. While important to the general consumer, fleet owners are most effected by vehicle prices and is their main cost alongside fuel. In the UK, government is providing incentives for EV's in a bid to make them more financially viable.

PHEV – As the PHEV combines both conventional combustions engines with electric motors the cost is substantially more compared to its counterpart. The most popular PHEV in the UK is the Mitsubishi Outlander PHEV (Mitsubishi 2016) with an average retail price for a high spec vehicle of £36,000 after grants. A similar spec Mitsubishi Outlander conventional combustion engine is around £30,000 (Mitsubishi 2016). The increase in cost is mainly down to the battery and the additional research & design and the electronics needed in the production of the vehicle. The battery alone costs in the region of £230 per kwh (Nykvist et Nilsson 2015) and while PHEV's batteries tend to be smaller than BEV the costs still add up as the capacity in the Outlander PHEV is 12kwh. Servicing costs are typically higher as well as specialist tools are needed.

E-REV – E-REV are typically less common than PHEV's or BEV's vehicle. Several manufacturers add in Range extenders as an additional option on standard BEV's such as in the BMW i3 which costs an additional £2900 to the base models £34,070 price tag (Car Buyer 2018) Current prices are difficult to find accurately due to the current lack of available models.

BEV – BEV's are increasing in popularity, this is a result of a rise in eco consciousness and also due to the reduction in cost thanks to lower battery production costs. Nykvist and Nilsson found that battery prices in 2015 were already below the target for 2017 (Nykvist et Nilsson 2015). A typical BEV (Nissan Leaf 30kwh 2016) costs in the region of £25,000 where as a comparable spec combustion vehicle (Nissan Pulsar) is around £19,000 (Nissan UK 2016). These costs are potentially offset in the future due to the running costs compared between the two types over a certain number of miles and the government grant provided for the EV (Nissan 2016).

HEV – HEV's have been around for a while now and as such their value is considerably less. They were introduced before the mainstream BEV's and since the increase in range allowance and PHEV's are becoming increasingly uncommon. Batteries are guaranteed for 8 years and operate at 30-80% SOC to reduce stress and large voltage changes, however they provide a high cost low density solution, nearly all today use nickel metal hydride batteries (Zhou et al. 2013) (Battery University 2016).

FCEV – FCEV's are relatively new technology and as a result their cost is typically very high. They are not readily available in most markets with the majority used currently in testing.

Many countries are offering incentives for Electric Vehicles in a bid to make them more appealing to the consumers. Jin et al. (2014) suggest that these incentives are important factors when trying to promote electric car sales. Outside the UK, countries such as China, employs tax incentives when purchasing an EV. Exemption from acquisition and excise taxes can range from £4500 - £7500. In European countries other examples of cost incentives such as in Norway include BEV's being exempt from VAT (Mock et Yang 2014). The UK government provides up to £4500 for cars and this increases up to £8000 for commercial vehicles (UK GOV 2016). The costs of batteries are a major reason why in general Electric vehicles are more expensive than their traditional internal combustion engine counterparts. Battery prices have recently hit their lowest cost for the last 9 years, and it is expected that as technology increases these costs will continue to drop. In 2013 the International Energy Agency (IEA) estimated that by the year 2020 battery prices will fall low enough so that Electric vehicle match conventional vehicles with a cost of £220 per kilowatt hour of capacity. However current cost has already met this target with a current price of just £200 per kwh a fall of 73% since 2007 when the price was £760 per kwh (US Department of Energy 2016) (International Energy Agency 2019). This information provides encouraging signs on the possibility to manufacturer batteries at low prices enabling EV's to be readily available to consumers at good prices.

5.6 Modelling

The Electric Vehicle Routing Problem (E-VRP) is a relatively new variant to VRP research. Although, recently with the increase in popularity in EV's in general, there has been a noticeable increase in research within the area. This section introduces the EV model and then provides the reader with additional factors that can then be included within the model to allow for a realistic representation. It is hoped that the information provided within this section will stimulate further research within the area.

5.6.1 A Hyper Realistic Electric Vehicle Energy Consumption Model

As mentioned previously the Electric Vehicle routing problem is a relatively recent variant of the traditional vehicle routing problem (VRP). Electric vehicles are becoming increasingly popular amongst individuals and companies as they provide an energy efficient alternative to traditional ICE (Internal combustion Engine) vehicles. An accurate model to predict and model the amount of power consumption for electric vehicles is of great importance when routing electric vehicles due to their strong dependence on range. The model needs to incorporate multiple factors that affect the battery in order to maximise the accuracy of the model. The proposed model here is an adapted one taken from that of X. Wu et al (2015), who also adopt much of their model on fundamental theories within physics, similar to that of Tanaka et al. (2008).

5.6.1.1 Base EV Model

The current model that is being created to include EV's is as follows. The model is set up in a similar way to the traditional VRPTW although a number of constraints are added along with varying objective functions. The following is a simple electric model with a homogenous fleet. Let N be a set of customers with demands of q_i for customer i $\in$ N, with time windows$[e_i, l_i]$. A vehicle may arrive before service time and wait to start service. An unlimited fleet of EV's is considered with capacity Q and battery capacity B. Vehicles must start and end at the depot. Let R be a set of recharging stations with an identical cost at each station. Travelling from customer i to customer j incurs a cost c_{ij}, travel time t_{ij} and energy consumption b_{ij}.

A route is feasible if:

- Each customer is visited once and only once (charging stations can be visited multiple times).
- The total demand does not exceed the vehicle capacity.

- The Battery always has positive charge along a route.
- Each time window is respected.

Let $h_{ij} = \alpha b_{ij}$ be the time required to charge the consumed energy b_{ij}, where $\alpha > 0$ is a proportionality factor. Also, let $H = \alpha B$ be the total time required to charge B units of energy. $(i_1, i_2, \dots i_k)$ are a set of sub paths with i_1 and i_k having to end at a depot, and intermediate values $(i_2, i_3, \dots i_{k-1})$ are all customers. The battery constraint can be created as follows.

$$\sum_{j=1}^{k-1} b_{i_j, i_{j+1}} \leq B \qquad (1)$$

Or

$$\sum_{j=1}^{k-1} h_{i_j, i_{j+1}} \leq H \qquad (2)$$

The Objective function seeks to minimise total routing costs with constraints mentioned before. This objective function contains a large number of variables that are different for each feasible route. The energy that is being used in this model b_{ij} between customer i to customer j must be calculated accurate. The model that is proposed in this thesis looks at extending that of X. Wu et al (2015) which is based on fundamental theories within physics. Our contribution follows as an extension which follows on from equation 15.

The instantaneous power of an EV is determined by vehicle speed, acceleration and the gradient. From basic physics the required tractive effort for all vehicles can be described using three major resistances:

$$F = ma + R_a + R_{rl} + R_g \qquad (3)$$

Where F is the tractive effort (in N), m is the vehicle mass (in kg), a is the acceleration (in m/s^2) and R_a, R_{rl} and R_g are the aerodynamic, rolling and grade resistances respectively (in N). R_a, R_{rl} and R_g can be calculated in the following equations:

$$\begin{cases} R_a = kv^2 = \frac{\rho}{2} C_D A_f v^2 \\ R_{rl} = f_{rl} mg \\ R_g = mgsin\theta \end{cases} \tag{4}$$

Where k is the aerodynamic resistance constant, determined by air density ρ (in kg/m^3), coefficient of drag is C_D and the frontal area of the vehicle is given by A_f (in m^2). f_{rl} is the rolling resistance constant and g is the acceleration of gravity (g = 9.81 m/s^2).

Combining Equations (3) and (4) above provides:

$$F = ma + kv^2 + f_{rl}mg + mgsin\theta \tag{5}$$

This equation shows the forces acting on a vehicle and can be used for both EV's and ICE vehicles. Extending this for the required power for a vehicle travelling at a specific velocity can be estimated using the following equation:

$$p = Fv = (ma + kv^2 + f_{rl}mg + mgsin\theta)v \tag{6}$$

p is the output power (in watts) of the vehicles provided by the input power P (in watts). EVs tend to have much higher efficiencies than standard ICE vehicles mainly due to their low power losses through the electrical motor. In an electric vehicle the efficiency is around 90-95%, This is given by an efficiency factor η.

$$p = \eta . P \tag{7}$$

Ignoring power losses from the vehicle's accessories at this point such as A/C and the heater. The majority of the power losses within an EV motor come from copper loss for the high current region in a DC motor or iron loss for an AC motor, (the majority of EV's use AC motors, due to benefits with regeneration, their ability to provide continuous power and their sheer simplicity amongst others). Ohm's law indicates that electrical power losses can be described as I^2r. Thus by reducing the current will result in greater resistive losses. Therefore, the efficiency factor η is given by:

$$\eta = \frac{(P - I^2 r)}{P} \qquad (8)$$

Where I is the current (in Amps) and r is the resistance of the conductor (in Ω).

Using Equations 4 through to 6 provides the EV's instantaneous power:

$$P = I^2 r + Fv \qquad (9)$$

The Force F is generated by the torque, τ of the motor. This can be further simplified as a product of the Armature constant K_a, magnetic flux ϕ_d and current I.

$$F = \frac{\tau}{R} = \frac{K_a \cdot \phi_d \cdot I}{R} \qquad (10)$$

Where τ is the torque (in Nm), R is the radius of the tire (in m), K_a is the Armature constant, ϕ_d is the magnetic flux (in webe) and I is the current (in amps). For AC and DC motors the magnetic flux is different, for a DC motor ϕ_d is determined by the current flowing through the armature coil and strength of the field magnets. For an AC motor ϕ_d is the rms value of the direct axis air gap per pole. We can therefore simplify equation 8.

$$K = K_a \cdot \phi_d \qquad (11)$$

When substituted into equation 10 gives:

$$F = \frac{K \cdot I}{R} \qquad (12)$$

When combining equations 3, 7 and 10 it provides an EV's instantaneous power estimation at speed v:

$$P = \frac{r \cdot R^2}{K^2} (ma + kv^2 + f_{rl}mg + mgsin\theta)^2 + v(kv^2 + f_{rl}mg + mgsin\theta) + mav \qquad (13)$$

This can be further broken down into the different losses as shown in equation (10).

$$P = P_m + P_{tr} + P_g \qquad (14)$$

$P_m = \frac{r \, . \, R^2}{K^2} (ma + kv^2 + f_{rl}mg + mgsin\theta)^2$ is the power losses by the motor, $P_{tr} = v(kv^2 + f_{rl}mg + mgsin\theta)$ is the power losses because of travel resistance and $P_g = mav$ is the possible energy that can be gained from acceleration.

X. Wu et al (2015) carried out model evaluations and tests on instantaneous the power consumption model and was concluded that it accurately estimated an EV's instantaneous power. The authors then continued to model the energy consumption over a whole trip. The total energy usage, E, which can be calculated by integrating the power, P, over the trip time, T.

$$E = \int_0^T P(t)dt \qquad (15)$$

This model provides good results with real life tests from Wu et al. (2015) with a mean absolute error (MAE) value of 15.6%. There is however potential to further adapt the model in order to create a more realistic model. Electric vehicles have additional factors that can effect power consumption and ultimately, range. As discussed in Chapter 5 Section 3.1 the Efficiency of the BEV can vary according to the Electric Motor Efficiency, the Drivetrain efficiency and the Battery Efficiency.

- The internal resistance within the battery r, changes with temperature ultimately altering the efficiency of the battery.

- The battery regeneration part of the equation has complex speed and SOC (state of charge) dependencies that manufacturers use. The battery cannot often enter regen mode when the battery is within 100-90% SOC due to the unnecessary increase in temperature. It also enters into different strength of regen at different speeds that was introduced by the manufacturer to make the car feel more natural when driving.

These can be incorporated into the model using results from research. As discussed before the internal resistance is largely affected by the temperature of a battery due to the ion movement. Battery temperature is related to charging times and can be largely affected by the weather also. We can look at adding our battery efficiency and battery regeneration into our instantaneous power so that now the instantaneous EV power found equation (14) can now be written as:

$$P = \eta_B (P_m + P_t + P_g + P_r) \qquad (16)$$

Where η_B is now the battery efficiency and P_r is the possible energy that can be gained from regeneration. Battery efficiency, η_B can be considered to be a function f of temperature $Temp$, as seen from our research and so we can break this down into the following.

$$\eta_B = f(Temp) \qquad (17)$$

$f(Temp)$ is a function of temperature that will have the limits to its efficiency when it is cold and when it is hot. Battery regeneration, P_r depends on several factors including speed, and the current state of charge and can be modelled as the following.

$$P_r = g(SOC) + P_{available} \qquad (18)$$

The regen power is a function g depending on the stage of charge (SOC) and the power available at the time $P_{available}$. We suggest that these two additions are investigated further with detailed breakdowns that then can be implemented into EV models allowing more accuracy when modelling. This accuracy is very important with EV's as much influence is based on their range. By incorporating the information that has been shown earlier a more realistic model can be created and it is hoped that future researchers can expand and apply the suggested model.

5.7 Summary

The chapter sheds light on various options and features of the green technology-based vehicles in terms of emissions related to transport industry. It is perceived that the range of alternative fuel powered vehicles is very diverse; carrying with them both advantages and disadvantages. As technology flourished consequently these characteristics may change, incorporating them within transport systems can not only provide better accuracy when developing transport routing strategies but they can also provide companies and policy makers with alternatives that can have a positive impact on the environment. The incorporation of a structured EV network is key when looking towards a greener future, examples demonstrated in this chapter highlight the importance of charging times and the recent advancements in technology, with upto a 68% change in emissions depending on the season and as much as a 33% change during a day. Combining the two can help reduce air pollution and help fight climate change. The study in this chapter is also meant to trigger further research on fleet management modelling investigating features and options that are not incorporated in previously developed relevant models.

Chapter 6

Conclusions

6.1 Research Summary

The VRP and CVRP have been around for over 50 years and as such have had extensive research performed on them. Solution methods including exact, heuristic and metaheuristic have been performed comprehensively and as such there is now little/no scope for improvement with many best-known solutions for the benchmark data sets to be considered solved to optimality. The results from the VNS are acceptable although it is predicted that with a stronger shaking procedure creating more varied neighbourhoods' further benefits can be achieved. The datasets that have been used in this thesis are from the Christofides et al. benchmark set (1979). Several researchers have tried to look at combining datasets and best-known values for a combination of different variants, however there is a lack of completeness, to the best knowledge the most up to date repository is maintained by Mendoza et al., (2014). The Green Vehicle Routing Problem is an area of great significance and the importance of providing clean air by reducing our emissions is forever growing. From the Literature gathered one can see the importance of the area, with governments and organisations imposing stricter regulations as well as providing their aims. We have provided several Platoon models and discuss several variants in detail. These platooning methods can allow large improvements in efficiency and although only small improvements have been shown so far with larger real life datasets it is hoped that this will increase when tested on more instances, particularly when datasets become clustered. With the introduction of driverless cars approaching the ability of platooning safely is a real possibility. We conducted a thorough

MPG experiment that can be used for future research to improve the accuracy of models, this is critical info that was based on real life data and tests. The extensive research on the battery technology applied to the VRP provides a great based for a new EV model, factors such as minimizing battery time left fully charged, regenerative braking and battery degradation from recharging have not been applied in the VRP area of research to the best of our knowledge. Papers surrounding the Electric VRP are minimal and as such only a few methods have been used to solve them and there is a gap for a range of heuristics and metaheuristic methods to be applied to this VRP variant. Accurate models for the energy consumption are key and sort after in literature with few taking all relevant factors into account. With most organisations looking to gradually invest in electric vehicles, replacing conventional vehicles with electric, a heterogeneous fleet is of great significance. Over-time has been overlooked in the electric vehicle routing problem, with the added option of over-time routes may be able to be optimised further.

6.2 Future research

Future suggested work includes the following.

- Further investigation into the splitting point within platooning, relaxing the forced platoons. Identifying these splitting points has been shown to be crucial when planning to platoon and further methods of identifying these will provide operators more options.

- Real life datasets should be created and applied to the platooning problem, where splitting points are confined to specific junctions on the main roads across the UK. With the routes confined to the actual roads there is further possibility of creating platoons and providing emission benefits.

- Further CFD modelling work on the air flow of HGV's when platooning should be explored. This will allow more accurate modelling for vehicles of different sizes and effect of platooning at different distances.

- Introduce the MPG experiment data into the models and also provide data for negative gradients.

- Apply the EV model with the additional factors mentioned in this thesis to datasets and compare to other models within research.

- Battery regeneration plays an important part for EV's, real-life examples of battery regeneration along with a detailed scientific model can be compared and applied to an EV model.

- Develop a new system that incorporates both platooning and electric vehicles. With the strict emissions policies and targets the UK are aiming for drastic measures need to be taken. Platooning and electric vehicles can both play a part in reducing these emissions and combining them will provide further benefits.

- Carry out platoon model testing on more datasets with the scope of allowing platooning multiple times during a vehicles route.

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Appendix

Appendix 1 Savings

1. Compute the savings $s_{ij} = c_{i0} + c_{0j} - c_{ij}$ for customers i, j, where $i, j = 1, \dots, n$ and $i \neq j$, c_{ij} is the cost of travelling from customer i to customer j. Create n vehicle routes $(0, i, 0)$ for $i = 1, \dots, n$. Order the savings in a non-increasing fashion.

2. (Sequential) Consider each route in turn, $(0, i, \dots, j, 0)$, define the first saving s_{ki} or s_{jl} that can feasibly be used to merge the current route with another route ending with $(k, 0)$ or starting with $(0, l)$. If feasible implement the merge and continue onto the next routes. If no feasible merge exists, consider the next route and apply the same operations. End when no feasible route merge is possible.

Appendix 2 VNS Algorithm

Initialisation:

Variables and matrices are defined. C factor is set as 1.

Data file is read and customers locations and demand are stored along with capacity constraint.

Starting times are set.

Capacity constraint is multiplied by the C factor value.

Initialise distance matrix

Calculate distance matrix

Initialise savings map

Calculate savings map

Create seed routes within initial routes matrix i.e 0-1-0, 0-2-0,...0-n-0 where n = number of customers.

Calculate the route demands

Calculate the routes length

Clarke and Wright Savings Method

Get the best nodes to connect from savings map

Find routes with the relevant nodes

Check the routes not to be equal

Merge the two routes

Repeat while savings map is not empty and initial routes matrix size !=1

Perform Intraroute swap

Selects the first customer of route 1 from a temporary routes matrix = to the initial routes matrix and tries to insert that customer into position 2, if shorter than previous route accept the route and set the initial routes matrix = temporary routes matrix, else temporary routes matrix = initial routes matrix e.g

```
if (temproutelength < temproutelength2)
{
routesMatrix[route] = temporaryroutesMatrix[route];
improvement = 1
}
else
{
```

```
temporaryroutesMatrix[route] = routesMatrix[route];
}
```

then proceed to try and move customer 1 to position 3, once all customers in the route have been selected and shuffled within their respective routes the program moves onto the next routes and repeats until all customers within all routes have selected and shuffled.

Calculate the tour lengths

End initial clock for initial solution

Set starting neighbourhood for heuristic procedures.

Output route configuration

Heuristic Start:

Set up starting parameters and matrices setting the current best to the initial solution – VNS and local matrix = initial matrix

K=0

VNS Loop k=k+1

> **Local Search Loop** (global improvement = false) if improvement is found within any local search routine this value becomes true, the local search loop will continue until this value has reached the end of the loop and is still false).
>
> > **Shift (2-0)** (select the first route, select the first customer, try inserting the first and second customer into another route in position1. If better update best routes matrix. Once the first two customers have been inserted into all the available positions within all available routes the best configurations

is chosen and saved as the starting point for the next shift (a check to remove null routes is also conducted at this point to ensure no errors occur), i.e first route second and third customer. Once the algorithm has passed through all the routes and tried to insert each pair of customers into each position the best configuration is saved as the local search matrix. Continue to carry out shift (2-0) until there is no further improvement after selecting each pair and inserting.

Finish clock for 2-0 shift

Intrarouteswap

Two opt

If better value is found when conducting 2-opt set new best = global best solution.

Accept the best of all solutions i.e once finished set the routes matrix = global best matrix

Three opt

If better value is found when conducting 3-opt set new best = global best solution.

Accept the best of all solutions i.e once finished set the routes matrix = global best matrix

Remove null routes

Output results

If new solution is better than previous then global improvement = true.

Insert (2-1) – same as previous shift (2-0) although also move one customer from route 2 into route 1.

Insert (1-0) – same as (2-0) although only moving 1 member from route 1 into other routes.

Swap (1-1) – swap a customer with another customer in another feasible route.

Swap (2-2) – same as (1-1) although swapping 2 adjacent customers at once.

Repeat until global improvement = false.

If the global best solution is better than the VNS best then update the Overall VNS Global best solution and matrix.

VNS Shaking select a random route and a random customer to be inserted a new route, using a temp routes matrix = Overall VNS global best matrix.

If k<50 then use new solution as a starting point for the local search loop and **repeat.**

Else set the routes matrix = Overall VNS global best routes matrix.

Two opt

Three opt

Output Route and store a file with graphical representation and full route information for best route matrix found.

Calculate the route emissions and the gallons of fuel used.

Store best solution within a set referenced by its capacity constraint. If user required **reduce** the C factor (capacity constraint) by 1% i.e 0.99 and recalculate the initial solution and **repeat all from data read.**

Output the best of the reduced capacity solutions and let user know which output file the best solution can be found.

Appendix 3 -Table 6.2-1. Passenger and Van emissions (DEFRA 2015)

			Diesel			
Activity	Type	Unit	kg CO_2e	kg CO_2	kg CH_4	kg N_2O
Cars (by size)	Small car	km	0.14367	0.14192	0.00008	0.00167
		miles	0.231214	0.228398	0.000129	0.002688
	Medium car	km	0.17561	0.17386	0.00008	0.00167
		miles	0.282617	0.279801	0.000129	0.002688
	Large car	km	0.2252	0.22345	0.00008	0.00167
		miles	0.362424	0.359608	0.000129	0.002688
	Average car	km	0.18232	0.18057	0.00008	0.00167
		miles	0.293416	0.290599	0.000129	0.002688
Vans	Class I (up to 1.305 tonnes)	tonne.km	0.61214	0.607749	0.000215	0.004175
		km	0.144477	0.143441	0.000051	0.000985
		miles	0.232514	0.230846	0.000082	0.001586
	Class II (1.305 to 1.74 tonnes)	tonne.km	0.633423	0.628961	0.000141	0.004321
		km	0.228331	0.226723	0.000051	0.001558
		miles	0.367463	0.364875	0.000082	0.002507
	Class III (1.74 to 3.5 tonnes)	tonne.km	0.502728	0.499203	0.000095	0.00343
		km	0.267749	0.265872	0.000051	0.001827
		miles	0.4309	0.427879	0.000082	0.00294
	Average (up to 3.5 tonnes)	tonne.km	0.529972	0.526249	0.000108	0.003615
		km	0.24999	0.248233	0.000051	0.001705
		miles	0.402319	0.399493	0.000082	0.002745
			Petrol			
			kg CO_2e	kg CO_2	kg CH_4	kg N_2O
Cars (by size)	Small car	km	0.15859	0.15807	0.00013	0.00039
		miles	0.255226	0.254389	0.000209	0.000628
	Medium car	km	0.19931	0.19879	0.00013	0.00039
		miles	0.320758	0.319921	0.000209	0.000628
	Large car	km	0.29074	0.29022	0.00013	0.00039
		miles	0.467901	0.467064	0.000209	0.000628
	Average car	km	0.19126	0.19074	0.00013	0.00039
		miles	0.307803	0.306966	0.000209	0.000628
Vans	Class I (up to 1.305 tonnes)	tonne.km	0.810251	0.806461	0.000831	0.002959
		km	0.190714	0.189822	0.000196	0.000696
		miles	0.306925	0.305489	0.000315	0.001121
	Class II (1.305 to 1.74 tonnes)	tonne.km	0.806109	0.802723	0.000743	0.002643
		km	0.2124	0.211508	0.000196	0.000696
		miles	0.341825	0.34039	0.000315	0.001121
	Class III (1.74 to 3.5 tonnes)	tonne.km	0.483084	0.479559	0.00041	0.003115
		km	0.257481	0.255602	0.000218	0.00166
		miles	0.414375	0.411352	0.000352	0.002672
	Average (up to 3.5 tonnes)	tonne.km	0.683723	0.6804	0.000647	0.002676
		km	0.20994	0.208919	0.000199	0.000822
		miles	0.337865	0.336223	0.00032	0.001322

Appendix 4 – CO_2 Experiment Data

Table 6.2-2 - MPG calculations

		Small Van No Load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	11.1	178.1	0	189.148	42.6
	1	11.1	178.1	207	396.31	33.6
	2	11.1	178.1	414	603.408	27.4
	5	11.1	178.1	1035	1223.7	20.9
8.94	0	44.4	178.1	0	222.437	51.4
	1	44.4	178.1	207	429.598	42.3
	2	44.4	178.1	414	636.697	36.1
	5	44.4	178.1	1035	1256.98	24
13.41	0	99.9	178.1	0	277.918	53.4
	1	99.9	178.1	207	485.08	42.7
	2	99.9	178.1	414	692.179	36.1
	5	99.9	178.1	1035	1312.47	25.6
17.8816	0	178	178.1	0	355.624	54.2
	1	178	178.1	207	562.786	47.8
	2	178	178.1	414	769.884	40.8
	5	178	178.1	1035	1390.17	25.1
22.35	0	277	178.1	0	455.459	53.8
	1	277	178.1	207	662.621	43.4
	2	277	178.1	414	869.719	37.1
	5	277	178.1	1035	1490.01	24.5
26.82	0	399	178.1	0	577.518	51.3
	1	399	178.1	207	784.68	40
	2	399	178.1	414	991.779	33.9
	5	399	178.1	1035	1612.07	24.3
31.29	0	544	178.1	0	721.77	40.3
	1	544	178.1	207	928.932	36.1
	2	544	178.1	414	1136.03	32
	5	544	178.1	1035	1756.32	21
35.76	0	710	178.1	0	888.214	33.1
	1	710	178.1	207	1095.38	29.7
	2	710	178.1	414	1302.47	26.1
	5	710	178.1	1035	1922.76	##

		Medium Van no load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	18.5	250.2	0	268.649	50.1
	1	18.5	250.2	291	559.703	35.3
	2	18.5	250.2	582	850.668	29.7
	5	18.5	250.2	1453	1722.15	18.2
8.94	0	74	250.2	0	324.13	67.8
	1	74	250.2	291	615.184	43.4
	2	74	250.2	582	906.149	30.6
	5	74	250.2	1453	1777.63	18.6
13.41	0	166	250.2	0	416.599	64.1
	1	166	250.2	291	707.653	44.7
	2	166	250.2	582	998.618	33.9
	5	166	250.2	1453	1870.1	19.8
17.8816	0	296	250.2	0	546.109	51.3
	1	296	250.2	291	837.163	40.3
	2	296	250.2	582	1128.13	33.5
	5	296	250.2	1453	1999.61	18.3
22.35	0	462	250.2	0	712.501	41.4
	1	462	250.2	291	1003.55	32.4
	2	462	250.2	582	1294.52	26.6
	5	462	250.2	1453	2166	18.4
26.82	0	666	250.2	0	915.933	38.1
	1	666	250.2	291	1206.99	31.7
	2	666	250.2	582	1497.95	25.6
	5	666	250.2	1453	2369.43	##
31.29	0	906	250.2	0	1156.35	33.1
	1	906	250.2	291	1447.41	26.1
	2	906	250.2	582	1738.37	22.2
	5	906	250.2	1453	2609.85	##
35.76	0	1184	250.2	0	1433.76	26.1
	1	1184	250.2	291	1724.81	21.7
	2	1184	250.2	582	2015.78	##
	5	1184	250.2	1453	2887.26	##

		Large Van no load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	22.6	273.7	0	296.309	26.5
	1	22.6	273.7	318	614.756	24
	2	22.6	273.7	637	933.107	22
	5	22.6	273.7	1590	1886.61	15
8.94	0	90.4	273.7	0	364.141	31.6
	1	90.4	273.7	318	682.588	26
	2	90.4	273.7	637	1000.94	24.2
	5	90.4	273.7	1590	1954.44	16.3
13.41	0	203	273.7	0	477.192	33.4
	1	203	273.7	318	795.64	28.1
	2	203	273.7	637	1113.99	26.4
	5	203	273.7	1590	2067.49	14
17.8816	0	362	273.7	0	635.53	35.6
	1	362	273.7	318	953.977	27.6
	2	362	273.7	637	1272.33	25.5
	5	362	273.7	1590	2225.83	14
22.35	0	565	273.7	0	838.959	35
	1	565	273.7	318	1157.41	28.1
	2	565	273.7	637	1475.76	26.2
	5	565	273.7	1590	2429.25	14
26.82	0	814	273.7	0	1087.67	35.1
	1	814	273.7	318	1406.12	28.5
	2	814	273.7	637	1724.47	24.2
	5	814	273.7	1590	2677.97	13.5
31.29	0	1108	273.7	0	1381.61	29.1
	1	1108	273.7	318	1700.06	21.7
	2	1108	273.7	637	2018.41	19.8
	5	1108	273.7	1590	2971.9	##
35.76	0	1447	273.7	0	1720.76	23
	1	1447	273.7	318	2039.21	19
	2	1447	273.7	637	2357.56	16
	5	1447	273.7	1590	3311.06	##

		Small Van 100kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	11.1	192.8	0	203.863	41.1
	1	11.1	192.8	224	428.145	32.4
	2	11.1	192.8	448	652.36	26.2
	5	11.1	192.8	1120	1323.91	19.2
8.94	0	44.4	192.8	0	237.152	50.5
	1	44.4	192.8	224	461.434	41.7
	2	44.4	192.8	448	685.649	35.5
	5	44.4	192.8	1120	1357.2	21.3
13.41	0	99.9	192.8	0	292.633	53.1
	1	99.9	192.8	224	516.916	43.5
	2	99.9	192.8	448	741.13	36.6
	5	99.9	192.8	1120	1412.68	24.5
17.8816	0	178	192.8	0	370.339	54
	1	178	192.8	224	594.622	46.2
	2	178	192.8	448	818.836	38.5
	5	178	192.8	1120	1490.39	24.2
22.35	0	277	192.8	0	470.174	53.6
	1	277	192.8	224	694.456	41.2
	2	277	192.8	448	918.671	36
	5	277	192.8	1120	1590.22	24
26.82	0	399	192.8	0	592.233	51.2
	1	399	192.8	224	816.516	38.5
	2	399	192.8	448	1040.73	33
	5	399	192.8	1120	1712.28	24
31.29	0	544	192.8	0	736.485	39.9
	1	544	192.8	224	960.767	35.8
	2	544	192.8	448	1184.98	31
	5	544	192.8	1120	1856.53	20
35.76	0	710	192.8	0	902.929	32.2
	1	710	192.8	224	1127.21	29.1
	2	710	192.8	448	1351.43	24.7
	5	710	192.8	1120	2022.98	##

		Medium Van 100kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	18.5	264.9	0	283.364	48.2
	1	18.5	264.9	308	591.538	34
	2	18.5	264.9	616	899.619	28.6
	5	18.5	264.9	1539	1822.36	16.6
8.94	0	74	264.9	0	338.845	66.4
	1	74	264.9	308	647.02	42
	2	74	264.9	616	955.101	28.7
	5	74	264.9	1539	1877.84	16.8
13.41	0	166	264.9	0	431.314	63.5
	1	166	264.9	308	739.489	43.2
	2	166	264.9	616	1047.57	32
	5	166	264.9	1539	1970.31	17.3
17.8816	0	296	264.9	0	560.824	50.8
	1	296	264.9	308	868.999	39.3
	2	296	264.9	616	1177.08	31.8
	5	296	264.9	1539	2099.82	17.5
22.35	0	462	264.9	0	727.216	41
	1	462	264.9	308	1035.39	31.8
	2	462	264.9	616	1343.47	25.2
	5	462	264.9	1539	2266.21	17
26.82	0	666	264.9	0	930.648	37.6
	1	666	264.9	308	1238.82	31
	2	666	264.9	616	1546.9	24.8
	5	666	264.9	1539	2469.64	##
31.29	0	906	264.9	0	1171.07	32.7
	1	906	264.9	308	1479.24	25.7
	2	906	264.9	616	1787.32	21.4
	5	906	264.9	1539	2710.06	##
35.76	0	1184	264.9	0	1448.47	25.8
	1	1184	264.9	308	1756.65	21.5
	2	1184	264.9	616	2064.73	##
	5	1184	264.9	1539	2987.47	##

		Large Van 100kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	22.6	288.4	0	311.024	25.4
	1	22.6	288.4	336	646.592	22.7
	2	22.6	288.4	671	982.058	21
	5	22.6	288.4	1676	1986.82	14.2
8.94	0	90.4	288.4	0	378.856	30.7
	1	90.4	288.4	336	714.423	25.2
	2	90.4	288.4	671	1049.89	23.2
	5	90.4	288.4	1676	2054.65	15.3
13.41	0	203	288.4	0	491.907	32.6
	1	203	288.4	336	827.475	27.2
	2	203	288.4	671	1162.94	25.2
	5	203	288.4	1676	2167.7	13.5
17.8816	0	362	288.4	0	650.245	34.7
	1	362	288.4	336	985.813	27.1
	2	362	288.4	671	1321.28	25
	5	362	288.4	1676	2326.04	13.3
22.35	0	565	288.4	0	853.674	34.2
	1	565	288.4	336	1189.24	27.2
	2	565	288.4	671	1524.71	24.9
	5	565	288.4	1676	2529.47	13
26.82	0	814	288.4	0	1102.39	34.5
	1	814	288.4	336	1437.96	27.8
	2	814	288.4	671	1773.42	23.2
	5	814	288.4	1676	2778.18	12.2
31.29	0	1108	288.4	0	1396.32	28.5
	1	1108	288.4	336	1731.89	21.3
	2	1108	288.4	671	2067.36	19.6
	5	1108	288.4	1676	3072.12	##
35.76	0	1447	288.4	0	1735.48	22.4
	1	1447	288.4	336	2071.05	18.6
	2	1447	288.4	671	2406.51	15.2
	5	1447	288.4	1676	3411.27	##

		Small Van 200kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	11.1	207.5	0	218.578	38.3
	1	11.1	207.5	241	459.981	30.3
	2	11.1	207.5	483	701.311	24.7
	5	11.1	207.5	1206	1424.12	18.6
8.94	0	44.4	207.5	0	251.867	46.8
	1	44.4	207.5	241	493.27	38.4
	2	44.4	207.5	483	734.6	32.8
	5	44.4	207.5	1206	1457.41	21.8
13.41	0	99.9	207.5	0	307.348	49.4
	1	99.9	207.5	241	548.752	39.2
	2	99.9	207.5	483	790.081	33.9
	5	99.9	207.5	1206	1512.9	23.4
17.8816	0	178	207.5	0	385.054	50.8
	1	178	207.5	241	626.457	44.4
	2	178	207.5	483	867.787	37.5
	5	178	207.5	1206	1590.6	23
22.35	0	277	207.5	0	484.889	50.8
	1	277	207.5	241	726.292	40.8
	2	277	207.5	483	967.622	34.3
	5	277	207.5	1206	1690.44	22.6
26.82	0	399	207.5	0	606.948	49.2
	1	399	207.5	241	848.351	37.7
	2	399	207.5	483	1089.68	31.5
	5	399	207.5	1206	1812.49	22.5
31.29	0	544	207.5	0	751.2	39.1
	1	544	207.5	241	992.603	34.4
	2	544	207.5	483	1233.93	29.9
	5	544	207.5	1206	1956.75	19.6
35.76	0	710	207.5	0	917.644	32.4
	1	710	207.5	241	1159.05	28.5
	2	710	207.5	483	1400.38	24.5
	5	710	207.5	1206	2123.19	##

		Medium Van 200kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	18.5	279.6	0	298.079	45.5
	1	18.5	279.6	325	623.374	32.1
	2	18.5	279.6	650	948.571	27.1
	5	18.5	279.6	1624	1922.57	16.4
8.94	0	74	279.6	0	353.56	62.3
	1	74	279.6	325	678.856	39.8
	2	74	279.6	650	1004.05	28
	5	74	279.6	1624	1978.06	17
13.41	0	166	279.6	0	446.029	59.9
	1	166	279.6	325	771.325	41.4
	2	166	279.6	650	1096.52	31.3
	5	166	279.6	1624	2070.53	18.3
17.8816	0	296	279.6	0	575.539	48.6
	1	296	279.6	325	900.835	37.8
	2	296	279.6	650	1226.03	31.1
	5	296	279.6	1624	2200.03	17
22.35	0	462	279.6	0	741.931	39.5
	1	462	279.6	325	1067.23	30.7
	2	462	279.6	650	1392.42	24.8
	5	462	279.6	1624	2366.43	17.1
26.82	0	666	279.6	0	945.363	36.9
	1	666	279.6	325	1270.66	30.2
	2	666	279.6	650	1595.85	24
	5	666	279.6	1624	2569.86	##
31.29	0	906	279.6	0	1185.78	32.4
	1	906	279.6	325	1511.08	25.1
	2	906	279.6	650	1836.27	20.7
	5	906	279.6	1624	2810.28	##
35.76	0	1184	279.6	0	1463.19	25.8
	1	1184	279.6	325	1788.48	21
	2	1184	279.6	650	2113.68	##
	5	1184	279.6	1624	3087.69	##

		Large Van 200kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	22.6	303.1	0	325.739	24.3
	1	22.6	303.1	353	678.428	22.1
	2	22.6	303.1	705	1031.01	20.3
	5	22.6	303.1	1761	2087.03	13.6
8.94	0	90.4	303.1	0	393.571	29.3
	1	90.4	303.1	353	746.259	24.1
	2	90.4	303.1	705	1098.84	22.2
	5	90.4	303.1	1761	2154.87	14.8
13.41	0	203	303.1	0	506.622	31.5
	1	203	303.1	353	859.311	26.2
	2	203	303.1	705	1211.89	24.2
	5	203	303.1	1761	2267.92	13
17.8816	0	362	303.1	0	664.96	34
	1	362	303.1	353	1017.65	26.2
	2	362	303.1	705	1370.23	23.9
	5	362	303.1	1761	2426.26	13.1
22.35	0	565	303.1	0	868.389	33.7
	1	565	303.1	353	1221.08	26.8
	2	565	303.1	705	1573.66	24.5
	5	565	303.1	1761	2629.68	##
26.82	0	814	303.1	0	1117.1	34.2
	1	814	303.1	353	1469.79	27.4
	2	814	303.1	705	1822.37	22.7
	5	814	303.1	1761	2878.4	##
31.29	0	1108	303.1	0	1411.04	28.7
	1	1108	303.1	353	1763.73	21.3
	2	1108	303.1	705	2116.31	19
	5	1108	303.1	1761	3172.33	##
35.76	0	1447	303.1	0	1750.19	22.9
	1	1447	303.1	353	2102.88	18.6
	2	1447	303.1	705	2455.46	##
	5	1447	303.1	1761	3511.49	##

		Small Van 500kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	11.1	251.6	0	262.723	28.6
	1	11.1	251.6	293	555.489	23
	2	11.1	251.6	585	848.165	18.4
	5	11.1	251.6	1462	1724.77	##
8.94	0	44.4	251.6	0	296.012	37.8
	1	44.4	251.6	293	588.778	29.2
	2	44.4	251.6	585	881.454	26.2
	5	44.4	251.6	1462	1758.06	##
13.41	0	99.9	251.6	0	351.493	39
	1	99.9	251.6	293	644.259	29.9
	2	99.9	251.6	585	936.936	26.2
	5	99.9	251.6	1462	1813.54	##
17.8816	0	178	251.6	0	429.199	39.6
	1	178	251.6	293	721.965	31.1
	2	178	251.6	585	1014.64	25.6
	5	178	251.6	1462	1891.25	##
22.35	0	277	251.6	0	529.034	40.5
	1	277	251.6	293	821.8	33.5
	2	277	251.6	585	1114.48	25.7
	5	277	251.6	1462	1991.08	##
26.82	0	399	251.6	0	651.093	40.3
	1	399	251.6	293	943.859	32.8
	2	399	251.6	585	1236.54	25.2
	5	399	251.6	1462	2113.14	##
31.29	0	544	251.6	0	795.345	32.8
	1	544	251.6	293	1088.11	30.6
	2	544	251.6	585	1380.79	##
	5	544	251.6	1462	2257.39	##
35.76	0	710	251.6	0	961.789	27.6
	1	710	251.6	293	1254.56	24.6
	2	710	251.6	585	1547.23	##
	5	710	251.6	1462	2423.84	##

		Medium Van 500kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	18.5	323.7	0	342.224	39.1
	1	18.5	323.7	377	718.882	27.5
	2	18.5	323.7	753	1095.42	23.2
	5	18.5	323.7	1881	2223.22	14.2
8.94	0	74	323.7	0	397.705	54.2
	1	74	323.7	377	774.363	34.7
	2	74	323.7	753	1150.91	24.5
	5	74	323.7	1881	2278.7	14.9
13.41	0	166	323.7	0	490.174	52.6
	1	166	323.7	377	866.832	36.7
	2	166	323.7	753	1243.38	27.8
	5	166	323.7	1881	2371.17	16.2
17.8816	0	296	323.7	0	619.684	43.1
	1	296	323.7	377	996.342	33.9
	2	296	323.7	753	1372.89	27.8
	5	296	323.7	1881	2500.68	15.4
22.35	0	462	323.7	0	786.076	35.2
	1	462	323.7	377	1162.73	27.5
	2	462	323.7	753	1539.28	22.1
	5	462	323.7	1881	2667.07	15.6
26.82	0	666	323.7	0	989.508	32.8
	1	666	323.7	377	1366.17	27.3
	2	666	323.7	753	1742.71	21.5
	5	666	323.7	1881	2870.5	##
31.29	0	906	323.7	0	1229.93	29.1
	1	906	323.7	377	1606.59	23
	2	906	323.7	753	1983.13	18.9
	5	906	323.7	1881	3110.92	##
35.76	0	1184	323.7	0	1507.33	23
	1	1184	323.7	377	1883.99	19.1
	2	1184	323.7	753	2260.54	##
	5	1184	323.7	1881	3388.33	##

		Large Van 500kg load				
Velocity (m/s)	Angle / Gradient	Ra (N)	Rrl (N)	Rg (N)	Total (N)	MPG
4.47	0	22.6	347.3	0	369.884	20.9
	1	22.6	347.3	404	773.936	19
	2	22.6	347.3	808	1177.86	17.4
	5	22.6	347.3	2018	2387.68	11.9
8.94	0	90.4	347.3	0	437.716	25.3
	1	90.4	347.3	404	841.767	20.8
	2	90.4	347.3	808	1245.69	19.2
	5	90.4	347.3	2018	2455.51	12.6
13.41	0	203	347.3	0	550.767	27.1
	1	203	347.3	404	954.819	22.4
	2	203	347.3	808	1358.75	20.8
	5	203	347.3	2018	2568.56	11.1
17.8816	0	362	347.3	0	709.105	29.2
	1	362	347.3	404	1113.16	22.6
	2	362	347.3	808	1517.08	20.7
	5	362	347.3	2018	2726.9	11.3
22.35	0	565	347.3	0	912.534	29.1
	1	565	347.3	404	1316.58	23.8
	2	565	347.3	808	1720.51	20.5
	5	565	347.3	2018	2930.33	##
26.82	0	814	347.3	0	1161.25	29.4
	1	814	347.3	404	1565.3	23.7
	2	814	347.3	808	1969.23	19.1
	5	814	347.3	2018	3179.04	##
31.29	0	1108	347.3	0	1455.18	25
	1	1108	347.3	404	1859.23	21
	2	1108	347.3	808	2263.16	16.2
	5	1108	347.3	2018	3472.98	##
35.76	0	1447	347.3	0	1794.34	20.7
	1	1447	347.3	404	2198.39	16.9
	2	1447	347.3	808	2602.32	##
	5	1447	347.3	2018	3812.13	##